



UNIVERSITY OF PATRAS

School of Engineering

Department of Mechanical Engineering & Aeronautics

Laboratory for Manufacturing Systems & Automation

PhD Dissertation

**A METHODOLOGY FOR DIGITALIZATION AND OPTIMIZATION
OF MILLING PROCESSES**

ATHANASIOS SOUFLAS

Mechanical & Aeronautics Engineer

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Advisory Committee

Panagiotis Stavropoulos, Associate Professor (Supervisor)

Dimitrios Mourtzis, Professor

Pantelis Nikolakopoulos, Professor

University of Patras, Department of Mechanical Engineering & Aeronautics

Souflas Athanasios

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To my parents, Vassilis and Ioanna

A METHODOLOGY FOR DIGITALIZATION AND OPTIMIZATION OF MILLING PROCESSES

ABSTRACT

The scope of the present research is to develop a methodology to support the digitalization of machining, focusing on the optimization of machining process quality, while ensuring their viability for industrial adoption. The current literature has been extensively studied, and three key digitalization barriers have been identified: (i) the disruption of the current workflow of the machining personnel, due to digital tools; (ii) the compatibility of existing approaches with legacy machine tools and (iii) the integration and operational complexity. These findings drive the technical objectives of this research, which has been executed in three main pillars, targeting different quality loss causes.

Pillar 1 focuses on the minimization of the machining load-induced error in robot machining. A Multi-Body Simulation of the machining robot has been developed, utilizing Reduced Order Models to minimize computational time. Based on synthetic datasets from this simulation, surrogate optimization techniques are developed, for workpiece placement and posture optimization during robot machining. The simulation and optimization software are tightly interfaced with CAM to minimize disruption of the current workflow of process planners. The benefits of the proposed tools in terms of dimensional accuracy and reduction of robot vibrations are demonstrated by machining a real component.

Pillar 2 focuses on the development of an in-process chatter detection system. A retrofittable monitoring setup is developed, based on an industrial accelerometer and DAQ, and is validated regarding the quality of the produced data. Features are extracted from the vibration signals in the frequency domain, where the energy shift of the signal from harmonic frequencies to chatter is tracked, and in the time domain, where the cyclostationary properties of the signal are investigated. The calculated features are input in a Support Vector Machine classifier that detects chatter with high accuracy. The generalizability of the approach is demonstrated through the installation of the system in multiple machine tools.

Pillar 3 focuses on the development of an in-process tool wear prediction system. Cutting force and temperature data from an instrumented milling head are used as a basis for tool wear estimation. By leveraging the machining theory on cutting force modelling, relevant features are extracted from the signals and used as input to a Decision Tree classifier to predict tool wear status and a Random

Forest regressor to predict the actual flank wear level. The generalizability of the approach is validated by exposing it to new, unknown datasets.

ΜΕΘΟΔΟΛΟΓΙΑ ΓΙΑ ΤΗΝ ΨΗΦΙΟΠΟΙΗΣΗ ΚΑΙ ΒΕΛΤΙΣΤΟΠΟΙΗΣΗ ΤΗΣ ΚΑΤΕΡΓΑΣΙΑΣ ΦΡΕΖΑΡΙΣΜΑΤΟΣ

ΠΕΡΙΛΗΨΗ

Ο σκοπός της παρούσας εργασίας είναι η ανάπτυξη μεθοδολογιών που μπορούν να υποστηρίξουν την ψηφιοποίηση της κατεργασίας φρεζαρίσματος, στοχεύοντας στη βελτιστοποίηση της ποιότητας της κατεργασίας, αλλά και διασφαλίζοντας τη δυνατότητα υιοθέτησής τους από τη βιομηχανία. Μετά από εκτενή βιβλιογραφική έρευνα εντοπίζονται τρία βασικά εμπόδια για την ψηφιοποίηση της κατεργασίας: (i) τα υπάρχοντα εργαλεία λογισμικού διαταράσσουν τον τρόπο με τον οποίο εργάζεται το προσωπικό σε μονάδες παραγωγής, (ii) οι υπάρχουσες προσεγγίσεις δεν είναι πάντα συμβατές με παλαιότερες εργαλειομηχανές και (iii) έχουν σημαντική πολυπλοκότητα στην ενσωμάτωση και λειτουργία τους. Με βάση αυτά τα ευρήματα, ορίστηκαν οι τεχνικοί στόχοι της ερευνητικής συνεισφοράς της διατριβής, η οποία εκτελέστηκε σε τρεις βασικούς πυλώνες, καθένας εκ των οποίων στοχεύει διαφορετικό λόγο που οδηγεί σε απώλεια ποιότητας.

Ο πρώτος πυλώνας εστιάζει στην ελαχιστοποίηση του σφάλματος κατά την κατεργασία που οφείλεται στις δυνάμεις κοπής κατά το φρεζάρισμα με ρομπότ. Αναπτύχθηκε μια προσομοίωση πολλαπλών σωμάτων, χρησιμοποιώντας τεχνικές αναγωγής του μοντέλου σε χαμηλότερη τάξη, με σκοπό τη μείωση του υπολογιστικού κόστους. Χρησιμοποιώντας δεδομένα από αυτή την προσομοίωση, αναπτύχθηκαν αλγόριθμοι βελτιστοποίησης, με σκοπό την εύρεση της βέλτιστης θέσης του εργατεμαχίου και της βέλτιστης πόζας του ρομπότ κατά την κατεργασία. Η προσομοίωση και οι αλγόριθμοι βελτιστοποίησης έχουν διεπαφές με το CAM, προκειμένου να χρησιμοποιούνται χωρίς να διαταράσσουν σημαντικά τον τρόπο εργασίας του προσωπικού. Τα πλεονεκτήματα των συγκεκριμένων εργαλείων λογισμικού, όσον αφορά τη διαστασιολογική ακρίβεια και μείωση των ταλαντώσεων του ρομπότ, αναδεικνύονται μέσω της κατεργασίας ενός πραγματικού εξαρτήματος.

Ο δεύτερος πυλώνας εστιάζει στην ανάπτυξη ενός συστήματος ανίχνευσης του φαινομένου του chatter. Αναπτύχθηκε ένα σύστημα παρακολούθησης των ταλαντώσεων της κατεργασίας, εύκολα ενσωματώσιμο σε υπάρχουσες εργαλειομηχανές, το οποίο πιστοποιήθηκε σχετικά με την ποιότητα των δεδομένων που καταγράφει. Από τα σήματα ταλάντωσης, εξάγονται χαρακτηριστικές τιμές στο πεδίο των συχνοτήτων (όπου παρακολουθείται η μεταφορά ενέργειας από αρμονικές συχνότητες, σε συχνότητες σχετιζόμενες με το chatter) και στο πεδίο του χρόνου (όπου παρακολουθούνται οι ιδιότητες κυκλοστασιμότητας του σήματος). Οι χαρακτηριστικές τιμές δίνονται ως είσοδοι σε ένα ταξινομητή, βασισμένο σε μια Μηχανή Διανυσμάτων Υποστήριξης, που ανιχνεύει το chatter με

μεγάλη ακρίβεια. Η δυνατότητα του συστήματος να γενικεύσει αναδεικνύεται μέσω τις εγκατάστασής του σε πολλαπλές εργαλειομηχανές.

Ο τρίτος πυλώνας εστιάζει στην ανάπτυξη ενός συστήματος πρόβλεψης του επιπέδου φθοράς του κοπτικού εργαλείου. Το σύστημα χρησιμοποιεί δεδομένα δύναμης και θερμοκρασίας κοπής, από μια φρεζοκεφαλή στην οποία έχουν ενσωματωθεί οι αντίστοιχοι αισθητήρες. Αξιοποιώντας τη θεωρία της κατεργασίας σχετικά με τη μοντελοποίηση των δυνάμεων κοπής, υπολογίζονται σχετικές χαρακτηριστικές τιμές από τα σήματα. Αυτές εισάγονται σε ένα ταξινομητή, βασισμένο σε Δέντρα Απόφασης, για την πρόβλεψη της κατάστασης του κοπτικού εργαλείου και ένα μοντέλο, βασισμένο σε Τυχαία Δάση, για την πρόβλεψη της ακριβούς τιμής της φθοράς της ελεύθερης επιφάνειας του κοπτικού εργαλείου. Η δυνατότητα του συστήματος να γενικεύσει αναδεικνύεται μέσω της δοκιμής του σε ένα νέο, άγνωστο σετ δεδομένων.

ABBREVIATIONS

Acronym	Explanation
MAPE	Mean Absolute Percentage Error
3D	Three Dimensional
CAM	Computer Aided Manufacturing
ADEV	Allan Deviation
FFT	Fast Fourier Transform
SVM	Support Vector Machine
ROC	Receiver Operating Characteristic
AUC	Area Under the Curve
DAQ	Data Acquisition device
CAGR	Compound Annual Growth Rate
AI	Artificial Intelligence
DT	Digital Twin
QA	Quality Assessment
SME	Small-Medium Enterprise
GPU	Graphics Processing Unit
OPC-UA	Open Platform Communications Unified Architecture
NGC	Next Generation Control
OEM	Original Equipment Manufacturer
CNC	Computer Numerical Control
TCP/IP	Transmission Control Protocol/Internet Protocol
API	Application Programming Interface
NC	Numerical Control
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
CAD	Computer-Aided Design
MBS	Multi-Body Simulation
ROM	Reduced Order Model
CECIMO	European Association of Manufacturing Technologies
FEM	Finite Element Model
CL	Cutter Location
DOF	Degree of Freedom
TCP	Tool Center Point
FRF	Frequency Response Function
EMA	Experimental Modal Analysis
FE	Finite Element

Acronym	Explanation
DH	Denavit-Hartenberg
CMS	Component Mode Synthesis
CB	Craig-Bampton
PD	Proportional-Derivative
RPM	Revolutions per Minute
PID	Proportional-Integral-Derivative
STEP	Standard for the Exchange of Product Data
STL	Standard Tessellation Language
BREP	Boundary Representation
ADAM	Adaptive Moment Estimation
URDF	Unified Robot Description Format
NURBS	Non-Uniform Rational B-Splines
LFC	Low Frequency Chatter
HFC	High Frequency Chatter
DDE	Delay Differential Equation
SLD	Stability Lobe Diagram
VMD	Variational Mode Decomposition
IMF	Intrinsic Mode Function
WPD	Wavelet Packet Decomposition
ASA	Angular Synchronous Averaging
MPE	Multiscale Permutation Entropy
MPSE	Multiscale Power Spectral Entropy
EEMD	Ensemble Empirical Mode Decomposition
PSE	Power Spectral Entropy
DFT	Direct Fourier Transform
CFRP	Carbon Fiber Reinforced Polymer
MEMS	Micro-Electromechanical System
RMS	Root Mean Square
ADC	Analog to Digital Converter
EMF	Electromagnetic Field
DC	Direct Current
AM	Additive Manufacturing
ANN	Artificial Neural Network
RF	Random Forest
KNN	k-Nearest Neighbour
LR	Logistic Regression
FPGA	Field Programmable Gate Array
RFB	Radial Basis Function

Acronym	Explanation
XML	Extensible Markup Language
5G	Fifth Generation telecommunications
MQTT	Message Queuing Telemetry Transport
BUE	Built-Up Edge
WC	Tungsten Carbide
WOA	Whale Optimization Algorithm
NPE	Neighborhood Preserving Embedding
CGI	Compacted Graphite Iron
ANFIS	Adaptive Neuro Fuzzy Inference System
PSO	Particle Swarm Optimization
PCA	Principal Component Analysis
LSTM	Long Short-Term Memory
PCBA	Printed Circuit Board Assembly
STU	Stationary Transceiver Unit
BLE	Bluetooth Low Energy
CAN	Controller Area Network
USB	Universal Serial Bus
HDF5	Hierarchical Data Format, Version 5
LRCS	Local Rotating Coordinate System
CS	Coordinate System
LNCS	Local Non-rotating Coordinate System
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error

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1. CHAPTER 1. INTRODUCTION

1.1. Background and Motivation

1.1.1. The Role of Digitalization in Modern Manufacturing

Over the last two decades, the manufacturing sector is being disrupted by the rapid advancement of digital technologies. The adoption of such technologies in different domains of the manufacturing sector, defined as digitalization or digital transformation of the sector, is moving beyond isolated automation initiatives and includes the integration of cyber–physical systems, industrial connectivity, data analytics, and artificial intelligence into every stage of the product manufacturing phase. This means that discrete technologies that have been emerging in academia and industry are now being part of an ensemble that is adopted as a whole and defines a data-driven approach towards production, enabling manufacturing companies to design, plan, monitor and control their production more efficiently [1.1].

Digitalization is at the forefront of industrial and academic research and innovation. It is not just being pursued by companies for the sake of following a trend. It is proven that it holds a strategic importance providing companies with tools and capacity to address some of the most pressing challenges of modern manufacturing.

- **Resilience:** The last decade has demonstrated the vulnerability of supply chains and production networks. Digitalization enables manufacturing companies to better anticipate potential disruptions, aggregating data from different sources in their value chain. Using this information, they can leverage the digitalization level of their production to perform data-driven decision-making on the reconfiguration that is needed to address the disruptions that are coming [1.2]. Studies have shown that companies in more digitalized industries have lost less revenue during the recent recessions (e.g. Covid-19 pandemic) [1.3].
- **Sustainability:** Manufacturing remains one of the major contributors to global greenhouse emissions and resource consumption. To this end, tightening regulatory frameworks are imposed on the manufacturing sector, related to energy usage, carbon emissions and resource utilization [1.4]. Additionally, potential resource scarcity poses the requirement for more sustainable and resource efficient manufacturing practices. Studies have shown a positive link between the digitalization level of a manufacturing company and its environmental performance. This positive link can be attributed to the ability to identify

inefficiencies, using aggregated data from the production and adapt production plans to achieve better resource utilization [1.5].

Apart from the aforementioned benefits, the usage of advanced digital tools in production facilitates consistent, high product quality and cost-efficiency, while achieving sustainability and resilience goals. The quality benefits from digitalization can be identified at process and machine levels. At process level, optimal process window identification, monitoring and control of the process through advanced digital tools, together with total quality control (i.e. 100% of manufactured parts being assessed for their quality) are enabled by advanced digital tools. On machine level, predictive maintenance tools, aggregating machine-generated data minimize downtime and scrap generated due to faults in the machinery [1.6]. Additionally, process and machine data that are generated during the manufacturing of a product and accompany it can be utilized to form new business models and add value for manufacturing companies. Servitization of manufacturing, which leverages these data, has been shown to improve the profitability of companies [1.7].

Considering the aforementioned, it is evident that digitalization can be the enabler for global competitiveness. It is not coincidental that all the major industrial markets are forming initiatives that define digitalization roadmaps for companies and secure funding for research and innovation around digitalization. Such initiatives include Industry 4.0 and 5.0 for Europe [1.8], Made in China 2025 [1.9], the Strategy for American Leadership in Advanced Manufacturing [1.10], and Japan's Industrial Value Chain Initiative [1.11].

Finally, the significance of digitalization in manufacturing is also evident from the size and growth rate of the digital manufacturing market. The digital manufacturing market has been valued at 392.80 billion USD in 2024, and it is estimated to reach 1.63 trillion USD by 2034, growing at a CAGR of 21.39% (Figure 1.1) [1.12]. Strong regional contributions from Europe, United States of America and China are observed, with USA being in a slight lead [1.13]. Technological segments, such as Digital Twins and AI-powered simulation are exhibiting significant growth (CAGRs of ca. 30-40%), showcasing the increasing industrial interest for such tools [1.12].

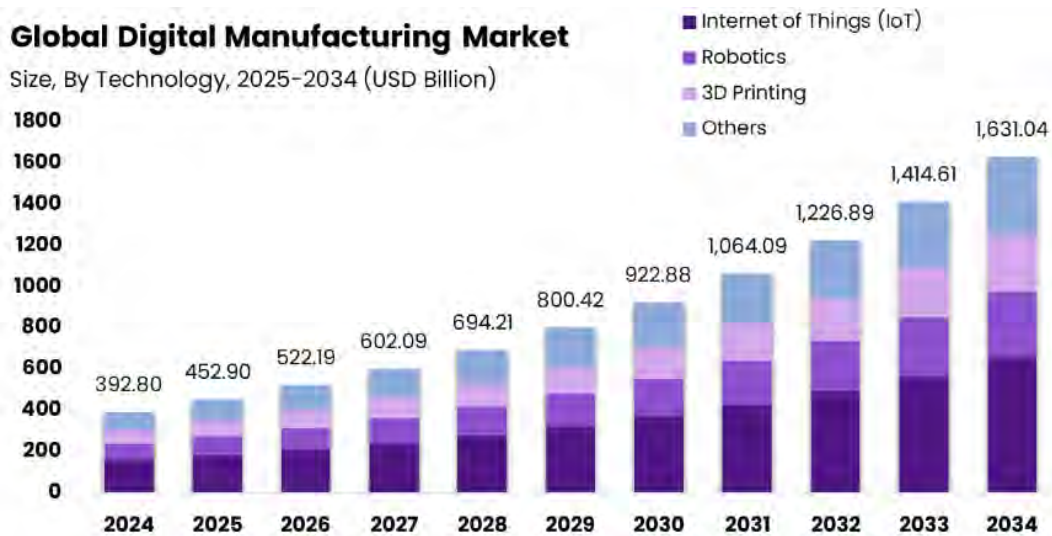


Figure 1.1 Digital Manufacturing market growth [1.12]

1.1.2. The Level of Digitalization in Machining

Within the broader context of the digital transformation of the manufacturing sector, the machining sector – covering milling, turning, drilling, grinding and other subtractive processes – presents a more complex adoption profile. Digitalization of machining is also seen as a key enabling technology for the future of the sector and the main targets for improving the process through digitalization are linked with the specific characteristics of the products manufactured typically through machining. Machining remains essential for producing high-precision, high-value components across industries such as aerospace, automotive, and energy. Machining is characterized by high quality requirements (tight dimensional tolerances, superior surface finish), complex geometries, and low to medium production volumes. These features demand a high degree of process reconfigurability and precision control, making digitalization a natural candidate for process enhancement [1.14]. The applications of digitalization in machining can be grouped into three main segments, namely machine tool virtual commissioning, process Digital Twinning, and traceability of quality in the machined products.

- **Virtual commissioning:** Virtual commissioning of machine tools requires the development of the digital representation of a machine tool, incorporating its geometric characteristics, kinematic and dynamic behavior. This virtual representation can be utilized for design optimization of individual machine tool components (spindle, frames, drives, etc.), as well as the overall machining system [1.15]. Apart from that, virtual acceptance testing of the final system can be achieved, reducing the time and cost for commissioning [1.16].
- **Digital Twins (DTs):** The term Digital Twins is utilized in academia and industry with an increasing rate over the last decade; however, it usually describes completely different approaches. By examining the vast landscape of available research works on the topic, significant variations can be observed in the granularity, accuracy, calculation speed and data

architecture of the DT [1.17]. The common denominator for all DTs, which differentiates it from the virtual representation of the process (e.g. a process model), is the requirement for a bilateral, real-time communication between the DT and the physical entity [1.6]. In the context of a machining process, DTs can support process planning, design space exploration, and prediction and compensation for effects such as tool wear, machine tool fatigue or thermal drift [1.18].

- **Traceability of quality:** In many cases, the products that are manufactured through machining are tied to total quality control. Nevertheless, full traceability on the root cause of quality reduction is often not possible. By aggregating data coming from different sources, internal to the machine (drive encoders, thermal sensors, power sensors, status signals, etc.) or external sensors retrofitted on the machine (vibration, force, sound, etc.), it is possible to create links between Quality Assessment (QA) results and identify systematic errors in the machine tool or process design [1.6].

These capabilities that are based on digitalization of machining, while increasingly feasible, are far from universally applicable. There are several barriers for adoption of digitalization, which can be grouped into three main categories:

1. **Resistance to change:** The use of very novel, different digital tools disrupts the workflow of the personnel in a machining company (process planners, CAM engineers, operators, QA testers, etc.). This creates an incentive against the adoption of new tools, even if their functionalities seem beneficial from a high level.
2. **Compatibility with legacy machine tools:** Most of the companies that operate machining machine tools, do not have equipment that is compatible with the Industrial Internet of Things (IIoT). Communication protocols might be vendor specific and machine tool controllers might be unable to share data with external applications hindering their connector with a wider digital thread. However, performance-wise these machine tools can be in excellent condition and might still be inside their service life, since IIoT-ready machine tools have emerged merely in the last decade. If the digital transformation of a company requires replacement of well-performing machine tools, solely because they are not IIoT-ready, then it is extremely difficult (if not impossible) to justify the investment cost [1.19].
3. **Integration and operational complexity:** Currently, academia favours overly complex approaches for applications, such as process modelling and especially monitoring and control. In order to implement these approaches, the skillset of an expert in the field is usually required. This skillset is not native to the personnel that comprises a machining company and, as such, a skills barrier is generated.

These barriers are especially prominent when Small-Medium Enterprises (SMEs) are considered. SMEs do not have the economic resources to perform large investments in IIoT (e.g. replacing their fleet). Additionally, they do not have the personnel capacity to dedicate people to train on novel

digital tools with steep learning curves. However, SMEs comprise over 80% of the European machining sector [1.20], playing a crucial role in the growth and sustainability of the sector.

1.2. Problem Statement & Research Contribution

The driving force behind this research is to contribute towards addressing these barriers for digitalization of the machining process, through the development of digital tools that target the optimization of the quality of the process. By diving deeper into each one of the barriers and analysing different studies on the topic, it is possible to identify specific objectives for the contribution of this research.

1. **Resistance to change:** As mentioned in the previous section, resistance to change is a result of the disruption that is caused by novel digital tools in the workflow of the machining personnel. This is mainly relevant in the process planning phase. While process simulation tools can provide valuable insight regarding the effect of process parameter selection in the final outcome (cutting forces, stability, surface generation), they are still conducted in standalone software tools and are not tightly interfaced with the CAM (the main software interface for a machining process planner). This creates a significant disruption in the workflow of the process planner and makes them more likely to resist adopting process simulation in their day-to-day work [1.21]. Next in the field of simulation is the computational cost of process models. Full-scale process models, incorporating machine tool behaviour and predicting complex phenomena, such as surface generation, have been proposed in the literature. Such models hold valuable information but come at a significant penalty in terms of computational time. The typical computational times for full-scale machining simulations might require several hours to simulate a few millimetres of cutting length [1.22]. Novel techniques, such as GPU-based acceleration of the computation [1.23] and combination of data-driven and physics-based methods [1.22], can reduce this time to less than an hour for a few millimetres of cutting length. These models are very beneficial in the design stage of a machine tool or a cutting tool but are not practical for the day-to-day operations of a machining process planner. On top of that, configuring and interpreting the results of such simulations requires very high expertise on the topic, which is not part of the skillset of a traditional machining process planner [1.24]. So, in response to this barrier, the requirements set for the research of this dissertation is to develop tools for simulation and optimization of the machining process that are tightly interfaced with the CAM software, utilize Reduced Order Modelling and data-driven methods to significantly reduce the computational time and enable the process planners to optimize their machining process, without requiring from them significant expertise on the topic of process simulation.
2. **Interoperability with legacy machine tools:** Many leading machine tool builders (DMG MORI, Mazak, Haas, Doosan, etc.) have now launched machine tools that are equipped with

industrial connectivity features. These machine tools incorporate open communication protocols such as MTConnect, OPC-UA and MQTT, enabling integration with third-party applications that utilise machine-generated data. Each brand markets its own digital ecosystem; examples include CELOS X from DMG Mori [1.25], SmartBox and MAZATROL iCONNECT from Mazak [1.26], and Next Generation Control (NGC) from Haas [1.27]. While these systems technically support standardised protocols, in practice, the deepest levels of machine data access and diagnostic capability are often tied to the proprietary platform of the OEM. This approach forces end users to adopt the software tools of the OEM, either through exclusive features or by licensing necessary protocol support only as part of a digital package. An exception to that are the machine tools that are equipped with the Siemens Sinumerik 840D CNC controller. Siemens provides native support for OPC UA, MTConnect adapters, PROFINET, and TCP/IP-based APIs through the Sinumerik Integrate suite, allowing direct access to NC variables, spindle loads, axis positions, alarms, and other operational data [1.28]. When these capabilities are fully enabled, third-party developers can connect directly to the CNC, bypassing the proprietary IoT platform of the OEM entirely. This makes it possible to build independent monitoring systems or Digital Twins without relying on brand-specific software and architectures. However, OEMs retain the ability to restrict access, e.g. by disabling network ports, limiting the set of accessible variables, or withholding the licenses needed for OPC UA servers. This allows them to establish a degree of platform lock-in. In practice, the openness of an IIoT-ready machine tool depends on a combination of control hardware capabilities, OEM policy, and licensing arrangements. Even when open protocols are supported, extracting rich, high-frequency process data for advanced monitoring applications may be challenging without the direct involvement and cooperation of the OEM. For the broader machining sector and particularly SMEs that operate diverse fleets including older machines, these constraints mean that the most reliable and brand-agnostic pathway to digitalization is retrofitting legacy and modern machine tools alike with external sensors and edge devices. By instrumenting machines independently of the control architecture of the OEM, manufacturers can establish unified, high-resolution data streams across mixed equipment, avoid vendor lock-in, and deploy digital manufacturing applications tailored to their specific operational needs. Based on this barrier, the requirements set for this research is to develop sensorization and digitalization approaches that are based on retrofitting existing machine tools, under the principle of minimal intervention, which will make them viable for industrial adoption.

3. Integration and operational complexity: It is evident already that integration of new systems to achieve the digitalization of machine tools is a difficult task. Selecting the simplest viable hardware and software architecture to achieve the needs of each specific application is crucial for a successful implementation, especially in the case of SMEs. On top of that, operational complexity needs to be considered [1.29]. Existing literature has proposed

several approaches that can achieve very good results but are based on overly complex algorithms that need significant user expertise to be configured. The recent evolution of Artificial Intelligence (AI) has sparked a race in academia to adopt very advanced AI models, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), etc. for process monitoring in machining. While the results are promising, very limited attention is brought to the ease of implementation and generalization of these models. In real industrial settings, it is not possible to generate and label the massive datasets required for training such AI models. Additionally, the generalizability of the models is seldom verified, by validating their performance across different machine tools, machining operations, materials, etc. [1.30]. This also comes in contrast with the industrial practice that calls for systems that can be trained with minimal data and be easily reconfigurable between different machining scenarios. These two industrial requirements are adopted as direct requirements for the research developed within this dissertation.

Figure 1.2 summarizes the digitalization barriers and how this dissertation contributes to addressing each one of them.

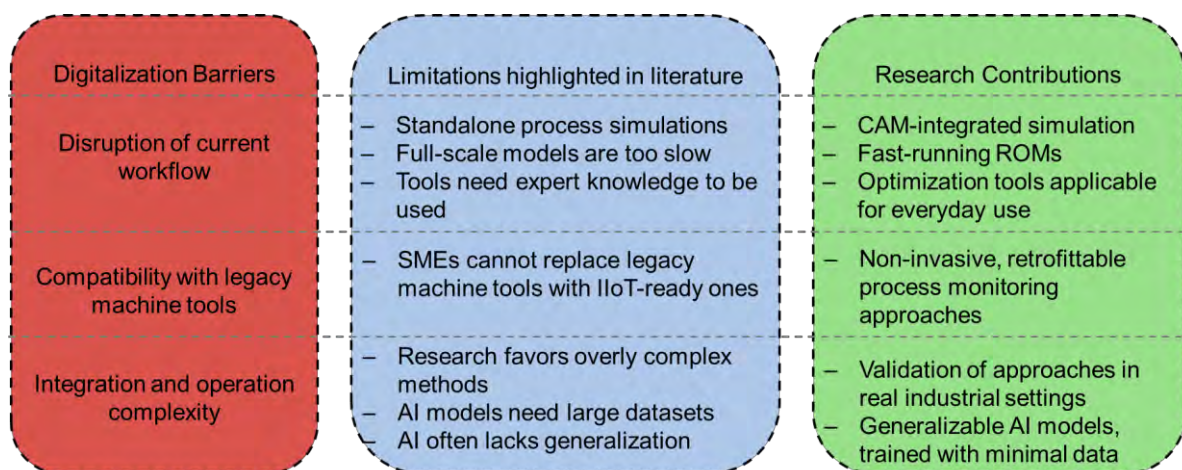


Figure 1.2 Barriers for digitalization of machining and contribution of this dissertation towards them

In summary, the contribution of the present research is to develop a methodology to support the digitalization of machining, focusing on the optimization of machining process quality, while ensuring their viability for industrial adoption.

To develop tools that aim to optimize the machining process quality, one can use the machining error as a way to quantify the loss of quality in the process. The machining error can be defined as the deviation between intended (CAD or nominal) geometry and the actual produced geometry. Several sources of machining error can be identified at different length scales (Figure 1.8).

- Micro-scale:
 - Surface roughness and topography: Small deviations in surface texture - characterized by parameters like R_a and R_q - affect friction, contact stiffness, and can act as nucleation sites for cracking or fatigue initiation [1.31]

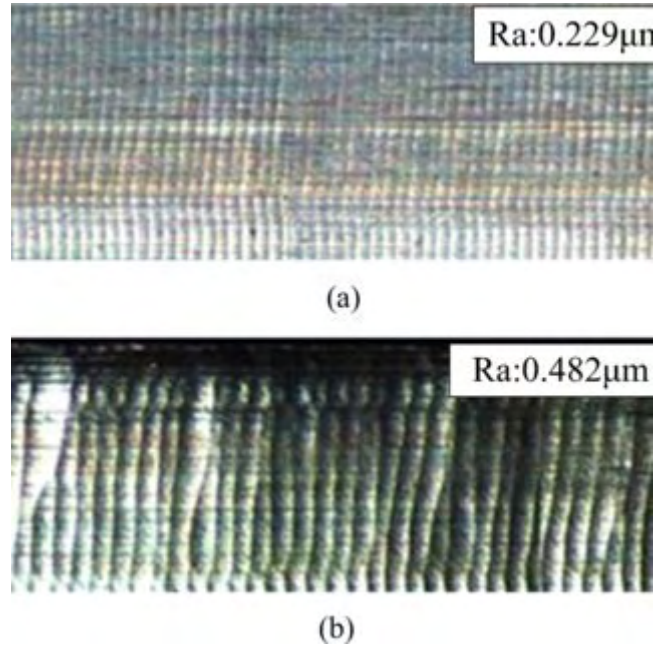


Figure 1.3 Typical topography of a machined surface [1.32]

- Microstructure changes and micro-deformation of grains: High mechanical loads and thermal exposure during cutting can trigger microstructural evolution - such as phase transformations and strain-induced grain refinement - altering material properties like hardness and ultimately impacting surface integrity [1.33]

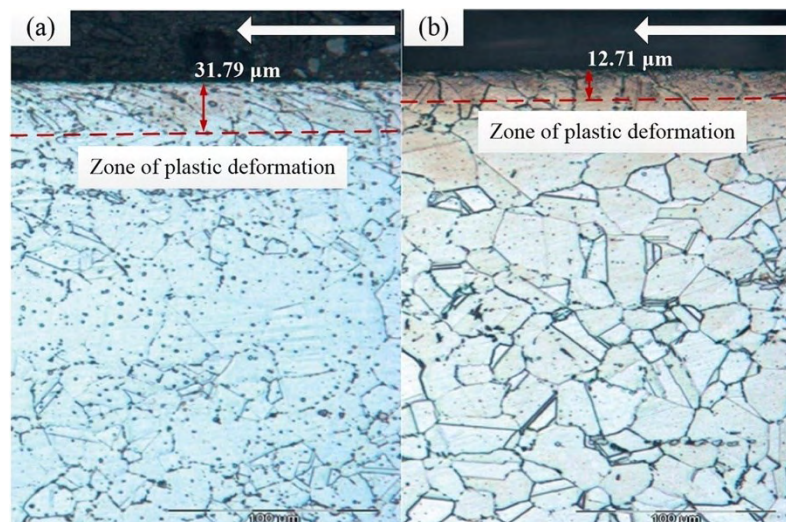


Figure 1.4 Effect of the machining process on the microstructure of the material [1.34]

- Residual stresses: Residual stresses often result from phase changes or deformation during machining and can lead to part distortion or dimensional inaccuracy over time. [1.33]
- Meso-scale:
 - Tool wear effects: Gradual wear (flank, crater, notching) alters tool geometry, leading to higher cutting forces, poorer surface finish, and increased dimensional error [1.35]

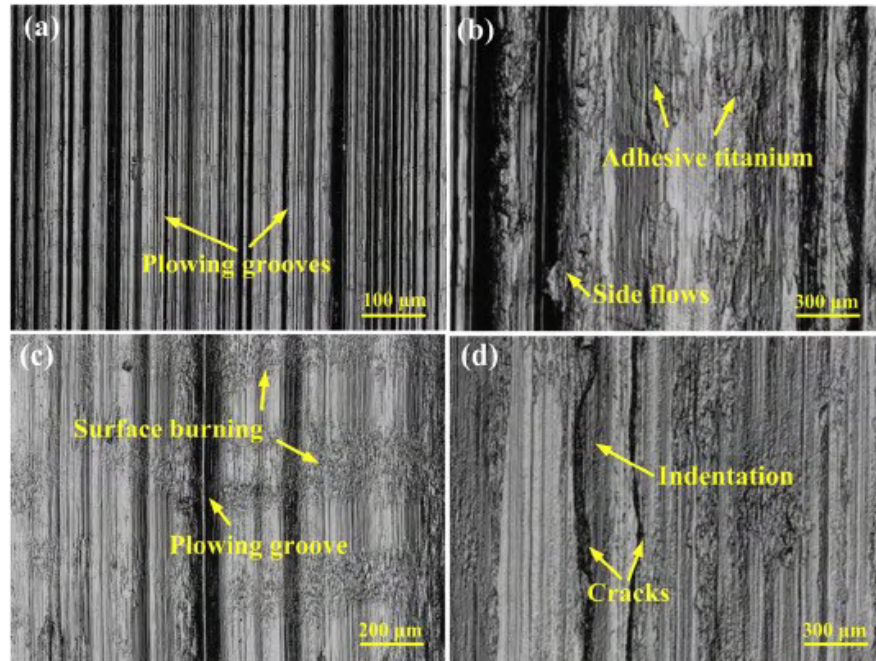


Figure 1.5 Machined surface defects at different flank wear levels: (a) $VB = 0.1$ mm (b) $VB = 0.2$ mm (c) $VB = 0.3$ mm (d) $VB = 0.3$ mm [1.35]

- Vibration-induced waviness: Forced excitations during machining produce characteristic surface waviness or cyclical deviations from nominal geometry [1.36]
- Local thermal distortions: Excess heat at the tool/workpiece interface causes local expansion and distortion, directly affecting machining dimensions and surface integrity [1.31].
- Chatter: When self-excited, regenerative vibrations develop, part surfaces suffer periodic deviations and tool life shortens [1.36]
- Macro-scale:
 - Global deflections under load: Cutting forces can cause structural deflections of the tool or workpiece. For example, long tool overhangs are prone to bending and deflection, degrading dimensional accuracy [1.37]

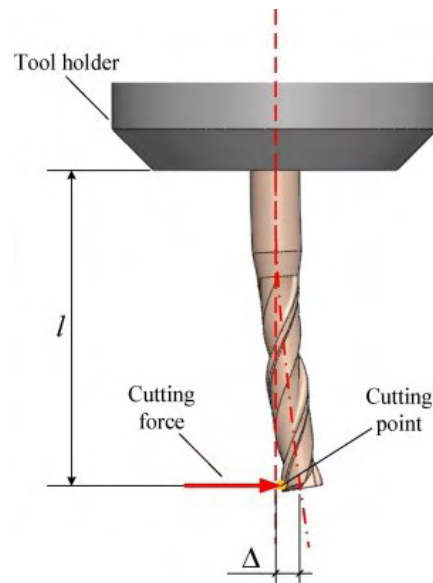


Figure 1.6 Machining error due to tool deflection [1.37]

- o Trajectory following errors: Dynamic errors arise when the actual toolpath deviates from the commanded trajectory - due to drive dynamics, acceleration/deceleration, or controller limitations - resulting in contouring inaccuracies [1.38]

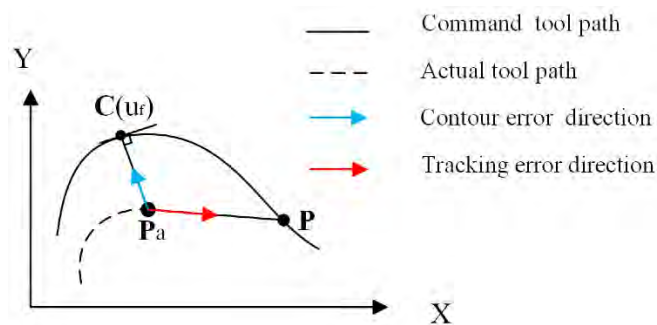


Figure 1.7 Trajectory following error in milling [1.38]

- o Setup/fixture alignment: Fixture misalignment, workpiece mispositioning, or kinematic errors in the machine's axes can directly translate geometric errors into the final part (e.g., squareness and axis parallelism issues)

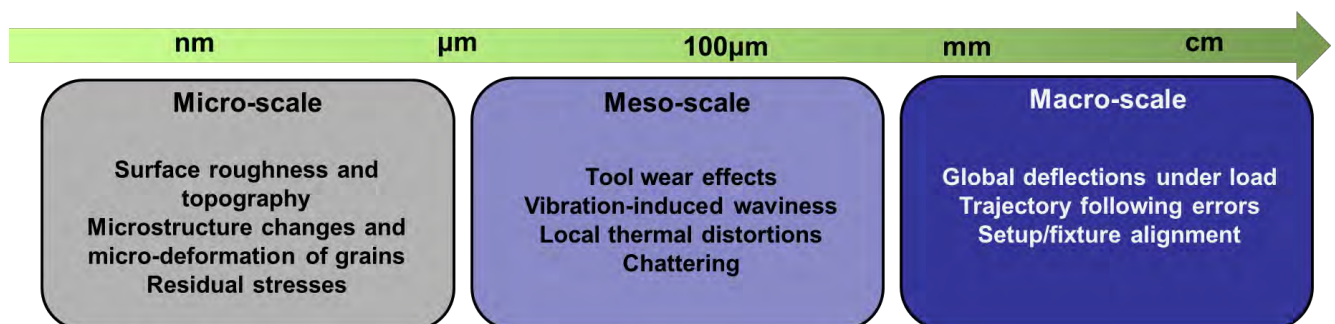


Figure 1.8 Summary of the sources of machining error at different scales

The contribution of this research is established under the following three pillars:

- Pillar 1 - Machining load-induced deformation minimization: This pillar refers to the development of Multi-Body Simulation (MBS) for prediction of the dynamic behaviour of a machining robot. The MBS utilizes ROMs to achieve low computational time and is tightly interfaced with the CAM software. Based on the MBS, surrogate optimization tools are developed to minimize the global deflections under machining load.
- Pillar 2 - In-process chatter detection: A monitoring system for the detection of chatter in the milling process is developed. It leverages data from a vibration sensor, and extracts features from these data that are fed to a Support Vector Machine model to detect chatter. The model is trained with minimal data and is tested for its generalization.
- Pillar 3 - In-process prediction of the tool wear level: A monitoring system for the real-time prediction of the flank wear is developed. It leverages cutting force and temperature data from a sensor-integrated milling head and extracts features from these data that are fed to a Decision Tree and Random Forest model to assess the tool condition. The models are trained with minimal data and are tested for their generalization.

1.3. Dissertation Structure

The rest of the dissertation is organized in the following chapters.

Chapter 2 presents the developments around the first pillar of the research contribution. It starts with a review of the State of The Art in dynamic behaviour modelling for robot machining, as well as a review of the approaches for workpiece placement and posture optimization. Next, the development of the MBS for the machining robot is presented in detail. The modelling approach and its assumptions are analysed, along with the software implementation of the model and the interface with CAM. Next, the surrogate optimization algorithms for workpiece placement and posture optimization are presented, along with their software implementation. The chapter ends with the presentation of the validation of these optimization algorithms in a real, case-study component.

Chapter 3 focuses on the second pillar of the research contribution. It starts with a review of the State of The Art on chatter monitoring in machining, focusing on the peculiarities of robot machining, compared to conventional CNC machining centers. Next, the monitoring system that has been developed is presented, along with a first evaluation of its performance, in terms of quality of measured data. Next, the analysis of the obtained signals is presented together with the methodology that is followed to extract chatter-related features from the signals. Finally, the development of the AI model and software implementation of the system for chatter detection is presented, together with a verification of its generalizability.

Chapter 4 is dedicated to the third and final pillar of the research contribution. It starts with a review of the State of The Art on tool wear monitoring in machining. Next, the monitoring system that has been adopted is presented. Next, the analysis of the obtained signals is presented together with the methodology that is followed to extract features from the signals, which are linked with the phenomenon of tool wear. Finally, the development of the AI models for tool wear level prediction are presented, together with a verification of their generalizability.

Finally, in Chapter 5, the contribution of this research is summarized, based on the results that have been achieved. The practical considerations for deployment of the outcomes of this research in industrial application are presented, along with the limitations that one might face. Based on these limitations, suggestions for future research pathways are made.

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2. CHAPTER 2. MINIMIZATION OF MACHINING LOAD-INDUCED DEFORMATION IN ROBOTIC MACHINING

2.1. Definitions

During a machining process, the deformation due to the machining load is a result of several compliance sources that are superimposed and can be viewed as a total deformation at the cutting tool tip. These compliance sources can be attributed to:

- Machine tool frame
- Spindle
- Bearings, guideways and transmission components of the machine tool and spindle
- Tool holder and cutting tool
- Receptance coupling between individual substructures

In specialized cases, the compliance of the workpiece itself might be dominant and require dedicated analysis. Such cases are met in machining of thin-wall components, such as aerospace blisks, but this is out of the scope of this work.

The assembly of the different components of a machine tool or a machining robot forms kinematic chains, which are closed in the case of the machine tool (Figure 2.1) and open in the case of the machining robot (Figure 2.2).

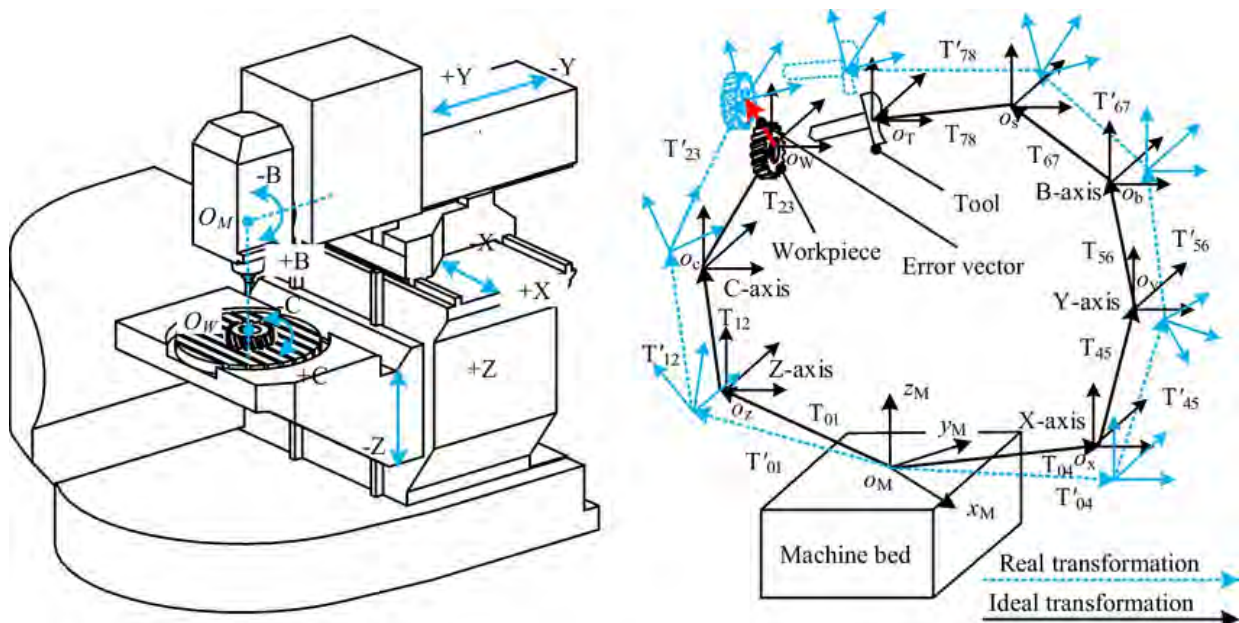


Figure 2.1 Structure and kinematic chain of a 5-axis machining center [2.1]

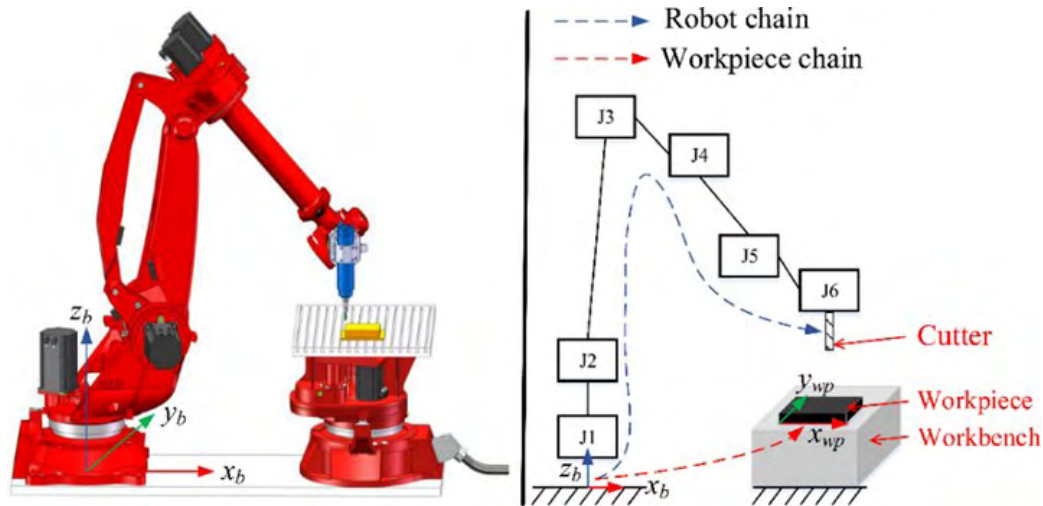


Figure 2.2 Structure and kinematic chain of a machining robot [2.2]

Depending on the position and orientation of the cutting tool, the substructures that comprise these kinematic chains are going to be loaded in different modes (bending, torsional, axial). As such, the way that each substructure resists the machining load-induced deformation needs to be calculated dynamically over the whole toolpath.

However, as an initial, rough estimation of the ability of a machine tool or a machining robot to resist deformation during the process, the global stiffness of the machine can be considered, which provides an overview of the ability of the machine to process different materials at different material removal rates (considering that the calculation of cutting forces is trivial). Essentially the global stiffness of the machine tool is another expression of Hooke's law and defines the stiffness of the machine in the three Cartesian axes as follows:

$$s_i = \frac{F}{\delta} \quad (2.1)$$

where:

- s_i is the global stiffness of the machine in axis i in (N/ μ m)
- F is a force applied along axis i in (N)
- δ is the total displacement measured at the tool tip along axis i in (μ m)

Typical global stiffness ranges for machine tools and robots are the following [2.3], [2.4]:

- 3-Axis Vertical Machining Centers:
 - X-axis: 15–25 N/ μ m
 - Y-axis: 15–25 N/ μ m
 - Z-axis: 70–100 N/ μ m
- 5-Axis Machining Centers:
 - X-axis: 7–15 N/ μ m

- o Y-axis: 7–15 N/ μ m
 - o Z-axis: 50–80 N/ μ m
- Industrial 6-DoF robots:
 - o Stiffness varies with posture, but a typical range for all axes is 0.1-1N/ μ m

There are two key takeaways from comparing machine tools and robots in terms of machining stiffness. Firstly, robotic arms are less stiff than machine tools by two orders of magnitude. This is inherent to their architecture as serial, open kinematic chains. Additionally, their stiffness varies with position and posture. Although a variation of stiffness in the working volume exists for machine tools as well - especially in large-scale machine tools - it can be approximated as consistent for most practical applications [2.5].

On the contrary, robotic arms exhibit significant variations in their working volume. This needs to be considered during process planning of machining and the process planner should try to place the workpiece and generate the toolpaths in such way that the robot gets the stiffest possible posture during the machining process. This is a highly non-trivial task, since the stiffness of the robot is not linear within its working volume. Additionally, there are other factors that should be considered, such as its kinematic performance. Despite the complexity of planning the machining process around the variable stiffness of the robotic arm, robots are gaining an increasing role as positioning systems for machining processes. The key benefits of robotic arms in the context of machining processes are the high flexibility and reconfigurability in processing complex geometries and varying workpiece sizes, the low investment cost compared to dedicated CNC machining centers and the much lower workspace footprint for the same working envelope [2.6]. As a result, robots are now undertaking post-processing tasks, such as deburring, polishing or drilling of large-scale castings and post-machining of large fiber-reinforced composite components [2.7]. Apart from these applications, industrial robots are being also utilized in 5-axis machining of components manufactured by materials with high machinability, such as marble or wood, for artwork or furniture manufacturing [2.8]. Recently, with the rise of electrification and the need for flexible approaches to machine aluminum battery pack casings, industrial robots are increasing their role in the automotive industry and are used to machine these components, thanks to their advantages, which have been described above [2.9].

The position of the robotic arm can have a significant effect on the achievable stiffness, both static and dynamic. Static stiffness refers to the global stiffness of a robot or machine tool, as expressed by equation 2.1, while the dynamic stiffness refers to the stiffness of the robot or machine tool as a function of the frequency of excitation. Figure 2.3 represents the variation of the static stiffness of the robot on a specific “slice” of its working envelope at the XY plane. A variation of more than 800N/mm with localized, high stiffness “islands” in the workspace of the robot can be observed. On the other hand, Figure 2.4 showcases the variation of the dynamic stiffness of the robot (in the form of the Frequency Response Function) at different postures. This means that the correct placement

of the workpiece is crucial and needs to be considered during process planning of a robot machining task. On the other hand, considering the orientation dependence, it has been proven that even at the same tool point location, different orientations yield stiffness characteristics. Exploiting this functional redundancy through intelligent posture planning has been shown to improve machining accuracy by up to tenfold, by aligning configurations to maximize stiffness or minimize deformation along the toolpath. In 5-axis milling with industrial robots, one Degree of Freedom (DoF) becomes redundant relative to positioning of the tool tip and orientation. By rotating around the tool axis, the robot can achieve configurations that differ in stiffness properties even as the Tool Center Point (TCP) location remains fixed. Studies by Celikag et al. [2.10] found stiffness variation of 58-161 % across redundant angles at fixed Cutter Locations (CLs), demonstrating the potential of posture optimization. An important consideration when developing optimization approaches for workpiece placement or posture planning during a machining toolpath is the kinematic limitations of the robot. Apart from respecting joint limits and considering only postures that have valid inverse kinematic solutions, the actual kinematic behaviour of the robot in the optimal stiffness solutions should be considered. Selecting solutions that result in large joint motions, velocities or accelerations between successive toolpath increments will lead to error in the end effector (either due to kinematic noise or due to excessive vibrations due to large joint motions), having an inverse effect in the machining performance [2.11].

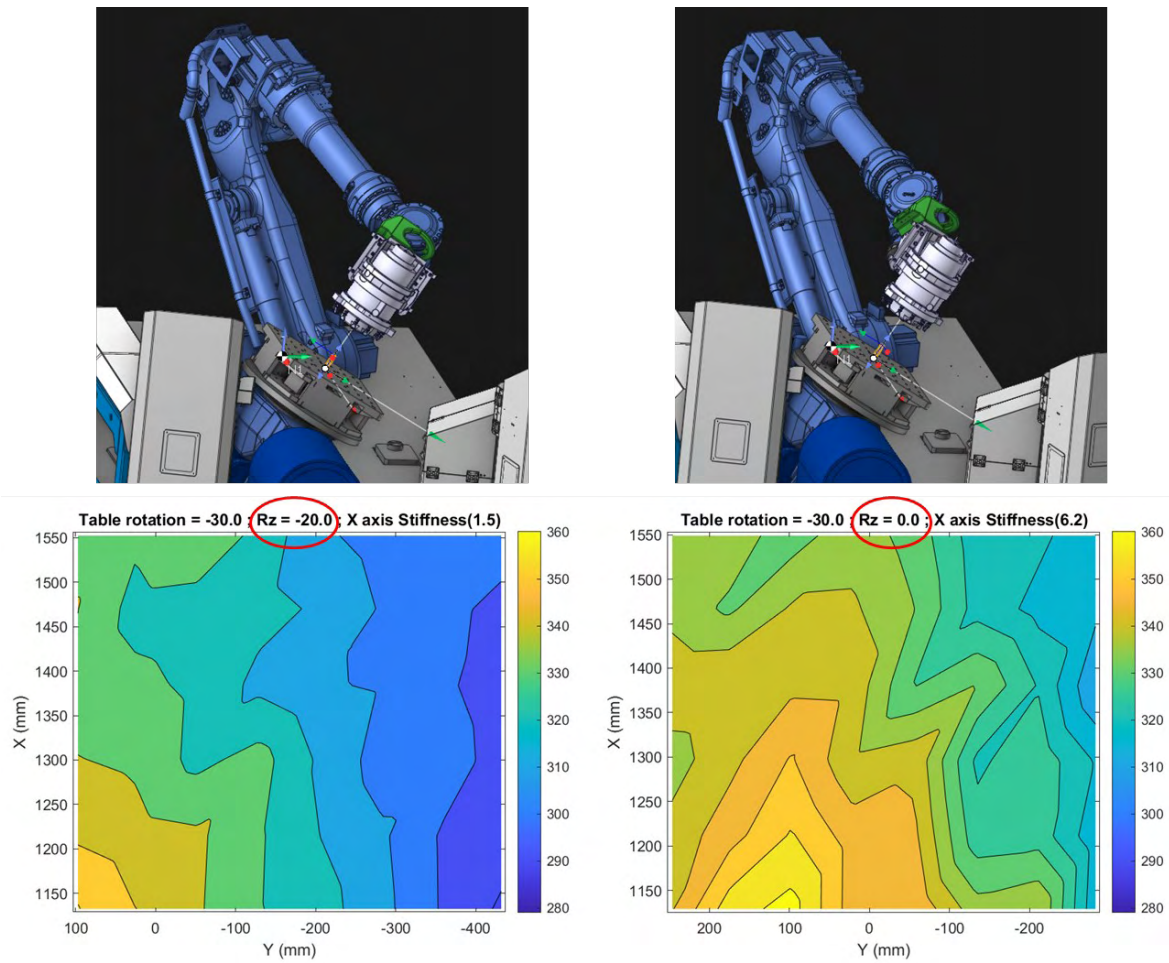


Figure 2.3 The effect of posture dependent in its static stiffness

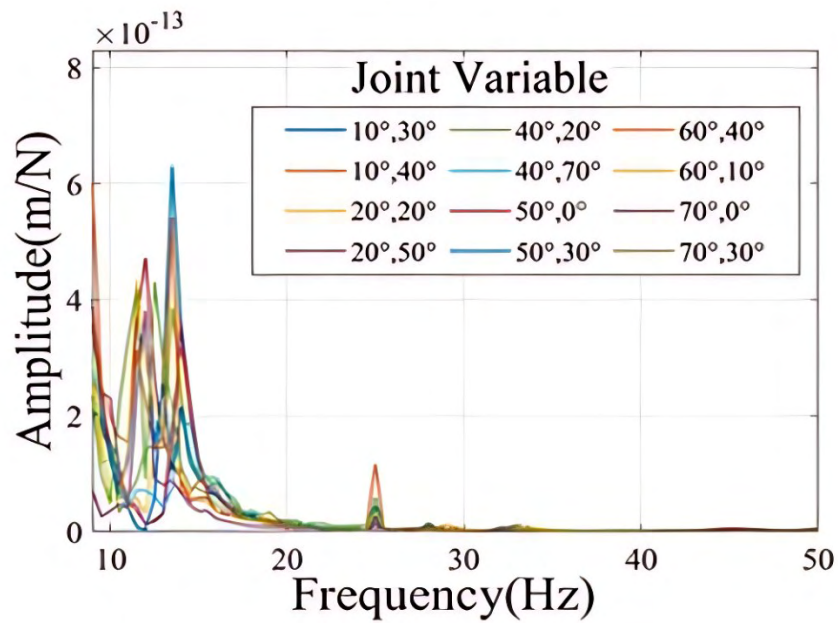


Figure 2.4 The effect of robot posture in its dynamic stiffness [2.12]

Considering the aforementioned, there is room for development of optimization tools that can support process planners in robotic machining processes, delivering high impact in the optimization of the quality of the machined part. To this end, this work focuses on developing tools for minimization of load-induced deformation in robot machining.

2.2. State of the Art in Robotic Machining Optimization

2.2.1. Simulation of the Dynamic Behaviour of the Robot

Since robot dynamics are of utmost importance for high-precision processes such as milling, there has been a wide range of publications in the literature that investigate the influence of robots' compromised structural stiffness and the mode shapes with low natural frequencies to the final process accuracy. Cordes et al. [2.13] investigated the process stability limits, concluding that for high-speed-machining operations, the pose-dependent modes of the tool-spindle system are the main source of instability, while the pose-dependent modes of the robot structure are causing the chatter at lower cutting speeds. Li et al. [2.14] investigated the relation between the effect of mode coupling chatter and the surface quality of the workpiece, finding that better results were obtained in cases where the feed motion of the cutting tool is along y -axis. Finally, they mentioned that proper workpiece placement can prevent chatter in robotic machining operations. Wu et al. [2.15] investigated the dynamic characteristics of a milling robots, using the R^2 -based compliance identification criterion, identifying joints as the compliance source of the milling robot, and subsequently characterized the robot mode shapes from the joint deformations. Finally, they identified the existence of weak excitation direction at the Tool Center Point (TCP). Mohammadi and Ahmadi [2.16] studied regenerative chatter when machining with robots that exhibit structural nonlinearities, using a two DOF vibratory system to model robot dynamics at the TCP, including cubic stiffness and damping terms to account for the robot's structural nonlinearities. Swan et al. [2.17] investigated the effect of low and high-frequency vibration modes in robotic milling, concluding that their parallel presence will lead to large surface accuracy error, but it is independent to the spindle speed. Tunc and Gonul [2.18] investigated the stability of robot milling operations, concluding that the vibration response of industrial robots under quasi-static motion conditions differs from that of static conditions, which in turn affects the stability limits at low-frequency chatter conditions. Finally, Busch et al. [2.19] attempted to quantify the uncertainties imported to the natural frequencies' prediction from the joint parameters used in the machining robot model.

To overcome the challenges and complexities introduced from robot posture-dependent dynamic behavior, several methods have been proposed in the literature. Huynh et al. [2.20] proposed a method to fit the elastic damping parameters of a MBS model used for a machining robot with flexible joints, using a genetic algorithm which was fed with data from Frequency Response Functions (FRFs) produced through impact testing. Chen et al. [2.21] proposed a method that uses several

measured FRFs and the inverse distance weight method, to predict the posture-dependent FRFs of a machining robot and generate the correspondent stability lobe diagrams. Chen and Ahmadi [2.22] proposed the combination of multibody dynamics and Gaussian Process Regression, to model the posture-dependent FRFs of machining robots, concluding that this approach presents more advantages compared to purely physics-based or data-driven methods. Wang et al. [2.23] proposed the use of a random forest based multimode prediction method to obtain the posture-dependent modal properties within the whole robot working space. Based on that, a multiple DOF dynamic equation was constructed and solved to predict the stability limits within the whole working area. Karim et al. [2.24] performed an extensive EMA for the measurement of robot dynamic behavior by performing experiments in the entire working space of the robot with different poses. Mejri et al. [2.25] also performed EMA to generate the stability lobe diagrams, observing that process stability is affected from the robot posture, the cutting tool orientation, and the feed direction. Xu et al. [2.26] presented a stiffness modelling method for robots, considering both joint and link compliances, in addition to the link weights and the gravity compensator. The model was later used for the calculation of deflections throughout the robot workspace, making it possible to estimate the contribution of external forces, link weights, and gravity compensator to the total deflections. Chen et al. [2.27] proposed an interactive coupling algorithm that integrated the robot dynamic model and cutting force model to predict the vibrations in robotic milling and assist the stability lobe generation process. For the robot dynamic model, only joint flexibility has been considered, and the rigid-flexible coupling dynamic model can be regarded as a superposition of rigid and flexible systems. Liao et al. [2.28] proposed a model that takes into account both the robot positioning error and the deformation error, introduced by the limited robot stiffness, for the prediction of the surface machining profile error. Additionally, a hierarchical error compensation algorithm that integrates offline and online approaches is introduced. Tepper et al. [2.29] developed the compliance model for an industrial robot considering the gear's stiffness parameters. For the aforementioned parameters' calculation, optimal design of experiments for variance-minimal Bayesian inference has been used. Finally, Doukas et al. [2.30] developed the finite elements (FE) model of the robot and used it to create its deflections map over its working space, to be used during the process planning stage.

2.2.2. Workpiece Placement Optimization

Using the knowledge of the dynamic behaviour of the robot (through simpler or more complex modelling approaches), it is possible to develop optimization algorithms to compensate for its position and posture-dependent stiffness. The two most common approaches in literature are workpiece placement and posture optimization. Workpiece placement optimization places and orients the workpiece in such a way, so that the robot will be at a region with high stiffness during the machining process. This is a global optimization approach. On the other hand, posture

optimization calculates the optimal values for the redundant degrees of freedom of the robot, so that it can assume the posture that maximizes stiffness (or other metrics) along a machining toolpath. In that case, the optimization can be point-by-point, regional or global. Starting with workpiece placement optimization, Qin et al. [2.31] proposed a method for optimization of the workpiece orientation in robotic milling. By considering the flexibility of the joints as the main source of compliance, they evaluate the quasi-static performance of the robot, by modelling the vibration-induced offset of the cutting tool, due to the machining loads. They optimize the workpiece orientation with the aim of minimizing the vibration-induced offset. Vosniakos and Matsas [2.32] have proposed a twofold optimization approach for identifying regions within the workspace of the robot for optimal workpiece placement, where manipulability is maximized and torques to resist the cutting loads are minimized. They utilize two genetic algorithms, one for each of the properties that is optimized. On a different note, Xue et al. [2.33] propose a base placement optimization for a machining robot, which operates on a movable platform and is targeted for large-scale components. Nevertheless, the principles of this approach are the same as in workpiece placement optimization for smaller components. They start by initializing a placement space for the robot base, so that the geometric center of the component is reachable. Then, by mapping the relationship between joint force and robot configuration, while considering the contour of the component, the optimal robot placement is selected, with the aim of global stiffness maximization.

2.2.3. Posture Optimization

Moving towards the domain of posture optimization, there is a higher number of works that can be found in the scientific literature. Xue et al. [2.34] developed a deformation evaluation index, which considers the stiffness values of each joint of the robot and the gravitational loads that are applied to the robot flange, due to the weight of the machining spindle. The index ignores the machining loads, as they are considered negligible compared to the spindle load. They solve the optimization of the redundant angle in 5-axis milling, utilizing Dijkstra search, while respecting a user-defined limit for the condition number of the Jacobian, to preserve kinematic quality of the solution. In a similar fashion, Xiong et al. [2.35] develop a stiffness model, considering the joints compliance as the main source of deformation, while modelling the links as rigid. Using this model, they are able to calculate the cartesian stiffness of the robot, based on the joint variables and they aim to optimize the redundant angle in 5-axis milling, by maximizing the robot stiffness in the feed direction. Through this method, they are able to achieve higher feed rate values, resulting in higher productivity. Ni et al. [2.36] formulated a piecewise-global optimization strategy incorporating stiffness, singularity avoidance, and joint limits. Instead of optimizing individual toolpath points, the toolpath is segmented and optimization of the redundant angle is performed, with the aim of stiffness maximization, while preserving pre-defined velocity limits for each joint and ensuring avoidance of singularities. Guo et al. [2.37] present a posture optimization method for robotic drilling applications.

Again, the aim is to optimize the angle of the end effector around the cutting tool axis, which is redundant. They use the stiffness ellipsoid as a stiffness performance index, which is proven to be frame invariant. They propose a novel solution method to maximize the index, based on the Jacobian matrix. By evaluating their approach in a case study of robotic drilling, they have measured up to 40% reduction in the deviation angle of the tool axis. Chen et al. [2.38] propose a posture optimization approach, based on a comprehensive deformation index, which considers the compliance of the joints as the main source of flexibility of the robotic arm, taking into account the gravitational loads due to the spindle weight and the cutting forces of the machining process. They find the optimal redundant angle, first for minimization of the deformation index, and next for minimization of the singularity index. Then, a genetic algorithm is utilized to approximate a global optimal solution for the whole toolpath. Cvitanic et al. [2.39] developed a static stiffness model, based on measured robot deflections under static loads and a dynamic stiffness model, based on impact testing of the robot at different configurations. Utilizing these models, they use exhaustive search to optimize the redundant angle towards minimizing the cutting force-induced deflection of the cutting tool. By comparing the static and dynamic approach, they concluded that dynamic models have reduced performance when process forces approach the eigenfrequencies of the robot. Lin et al. [2.40] proposed a combined approach for workpiece placement and posture optimization in robotic milling. Starting from the global available solutions within the workspace of the robot, they perform a refinement using a kinematic performance map and then a workpiece placement optimization using the stiffness map of the robot. Next, through a deformation evaluation index, they perform posture optimization, utilizing the redundant axes of the robot and rotary table, where the workpiece is mounted. In a case study, they managed to reduce the machining-induced deformation by more than 50%. On a different note, Mousavi et al. [2.41] presented an approach for optimization of the redundant angle towards machining stability. By calculating the posture-dependent Frequency Response Functions (FRFs) of the robot, they were able to identify the values of the redundant angle that will render the process unstable. They created three-dimensional stability lobes, taking into account also the redundant angle, apart from spindle speed and depth of cut.

2.3. Multi-Body Dynamic Simulation of the Machining Robot

2.3.1. Robot Kinematics

For machining operations, the CL data that are generated from the CAM system are usually expressed in the workpiece frame and require transformation to the robot frame before the process execution [2.13]. The homogenous transformation of the workpiece frame relative to the robot base frame is the following:

$$\overrightarrow{_{wp}^bT} = \overrightarrow{_{wb}^bT} * \overrightarrow{_{wp}^{wb}T} \quad (2.2)$$

where $\overrightarrow{_{wp}^bT}$ is the transformation from the workpiece frame to the robot base frame, $\overrightarrow{_{wb}^bT}$ is the transformation between the workbench frame and the robot base frame, and $\overrightarrow{_{wp}^{wb}T}$ is the transformation between the workpiece frame and the workbench frame. An example of the aforementioned frames is depicted in Figure 2.2. Additionally, in the robot kinematic chain, the transformation matrix of the tool tip frame relative to the robot base frame is calculated as follows:

$$\overrightarrow{_{tool}^bT} = \overrightarrow{_1^bT} * \overrightarrow{_2^1T} * \overrightarrow{_3^2T} * \overrightarrow{_4^3T} * \overrightarrow{_5^4T} * \overrightarrow{_6^5T} * \overrightarrow{_{tool}^6T} \quad (2.3)$$

where 1–6 represent the joint numbers, respectively. The Denavit-Hartenberg (DH) approach has been used for the calculation of the transfer matrices between the adjacent coordinate systems, and the transformation matrix $\overrightarrow{_{i-1}^i T}$ can be formulated as:

$$\overrightarrow{_{i-1}^i T} = \begin{bmatrix} \cos \theta_i & -\sin \theta_i \cos a_i & \sin \theta_i \sin a_i & a_i \cos \theta_i \\ \sin \theta_i & \cos \theta_i \cos a_i & -\cos \theta_i \sin a_i & a_i \sin \theta_i \\ 0 & \sin a_i & \cos a_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (2.4)$$

Combining Equations (2.2) and (2.3), the transformation of the tool frame relative to the workpiece frame can be expressed as:

$$\overrightarrow{_{tool}^{wp}T} = [\overrightarrow{_{wp}^bT}]^{-1} * \overrightarrow{_{tool}^bT} \quad (2.5)$$

After having defined the workpiece placement position and the CLs along the toolpath, the robot joint values throughout the process can be calculated using the inverse kinematics of the robot as follows:

$$\theta = IK(x_{wp}, y_{wp}, a_{wb}) \quad (2.6)$$

where $\theta = [\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6]^T$ is the motion of the robot joints, (x_{wp}, y_{wp}) is the positional offset of the workpiece from the workbench, and a_{wb} is the rotational offset of the workbench relative to the robot base frame [2.42].

2.3.2. Robot Dynamics

The Multi-Body Simulation methods have been adopted extensively for robot dynamic behavior modeling and simulation because of their high accuracy levels and time efficiency when compared to other simulation methods such as finite element. The two main approaches adopted for the modeling of the dynamic behavior of industrial robots are: (a) flexible joints and rigid links and (b)

both flexible joints and links. For the model presented in this work, the second modeling approach has been adopted, combined with the component mode synthesis (CMS) method, to enable accurate simulation of robot dynamics, while keeping the computation time in acceptable limits for usage during the process planning stage.

In general, the equation describing the robot dynamics for a specific configuration x_0 in the Cartesian space can be expressed as follows:

$$M_x(x_0)\ddot{\vec{\delta}}_x(t) + C_x(x_0)\dot{\vec{\delta}}_x(t) + K_x(x_0)\vec{\delta}_x(t) = \vec{F}(t) \quad (2.7)$$

where $\vec{\delta}_x(t)$, $\dot{\vec{\delta}}_x(t)$, $\ddot{\vec{\delta}}_x(t)$ are the displacement, speed, and acceleration of the end-effector, respectively, with $\vec{\delta}_x(t) = \vec{x}(t) - \vec{x}_0$ the infinitesimal displacement relative to a configuration $\vec{x}_0$; additionally M, C, K are the robot mass, damping, and stiffness matrices, respectively, and $\vec{F}(t)$ the cutting force vector applied to the cutting tool throughout the process. Moving on to the natural frequencies and mode shapes of the robot arm structure, they can be calculated using the following equation:

$$(K - \omega_{0i}^2 M)p_i = 0 \quad (2.8)$$

where ω_{0i} are the natural frequencies and p_i the mode shapes of the robot.

2.3.2.1. Robot Links Modelling

When link flexibility must be taken into account, FE models have been proven to be an accurate solution, using a significant number of degrees of freedom (DOFs) to calculate the link deflections. However, the number of DOFs used to represent the flexible link must be decreased before their integration with the MBS, to keep the computational cost low. For this purpose, the Craig-Bampton method has been utilized to build the reduced order model of each link [2.44]. The modelling process followed for the links of the robot is presented extensively below.

First, the FE models of all links must be created, so their elastic behaviour under loading conditions, in addition to their natural frequencies and mode shapes can be considered. Following that, the reduction of the models can be performed using the Craig-Bampton (CB) method. The advantage of this method is that it includes both static and vibration modes to create a complete reduction basis and, subsequently, an appropriate representation of the subsystem's dynamic behaviour. Only vibration modes with natural frequencies in a selected frequency range from the user are retained to approximate the dynamics of the DOFs internal to the substructure, leaving behind only the DOFs at the interfaces, which in this case are connected to the adjacent links through rotational joints, and a certain number of internal DOFs related to the retained vibration modes in a clamped boundary configuration. After the CB method application, the reduced mass and stiffness matrices are

obtained, which are known as Superelements in commercial FE packages and are being used to represent the dynamic behaviour of flexible bodies [2.45]. The modelling procedure for the robot links is summarized in Figure 2.5 below.

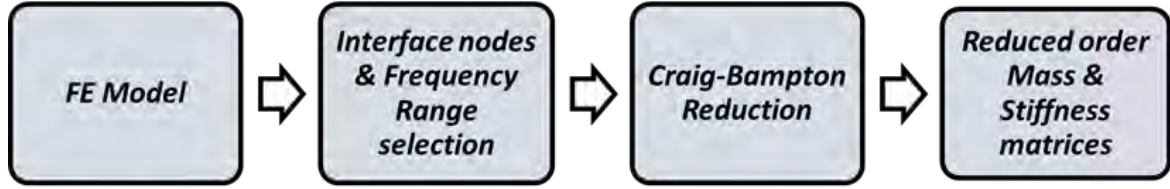


Figure 2.5 Modelling procedure for links flexibility

Finally, modal damping has been adopted to represent the damping properties of the links, and the damping matrix of every link can be formulated as follows:

$$[C] = [M][\Phi][2\zeta\omega_n][\Phi]^T[M] \quad (2.9)$$

where $[M]$ is the mass matrix, $[2\zeta\omega_n]$ is a diagonal matrix, and $[\Phi]$ are the mode shapes of the link substructure.

2.3.2.2. Robot Joints Modelling

Joint elastic behavior has been identified by many authors as one of the main sources of end-effector positional error during robotic machining operations, affecting directly the process accuracy, and it cannot be neglected. Assuming that joints' elastic deformation under loading conditions is a function of their stiffness and damping properties [2.46], the revolute joint of a robot can be modeled as a rotary spring-damper system along its rotation axis. The benefits of this modeling approach is that it can be fully described with only two parameters (spring stiffness and damping coefficient), while no considerable advantages from the use of more complex models with numerous parameters have been identified from the literature [2.47]. Additionally, the influence of servo motors' inertias has also been taken into account during the modeling phase for the sake of completeness.

It is important at this point to explain a bit further the approach used to include the joint deformations inside the MBS. In general, the applied joint motor torques can be calculated as follows:

$$\vec{\tau} = \vec{\tau}_m + \vec{\tau}_{ext} + \vec{\tau}_f \quad (2.10)$$

where $\vec{\tau}_m$ are the torques demanded to hold position or cause a motion, $\vec{\tau}_{ext}$ the resultant torques from external forces or torques that must be defeated, and $\vec{\tau}_f$ the friction-induced torques. However, since the robot controller does not receive any information regarding the cutting forces applied to the robot during the process and the joint position encoders are placed before the compliant transmission elements, the external forces exerted on the robot end-effector cannot be

compensated, leading to joint deformation and, subsequently, to process accuracy loss. The torques applied to joints for a given set of cutting forces can be calculated using the transpose of the robot arm geometric Jacobian as follows [2.48]:

$$\overrightarrow{\tau}_{ext} = J(q)^T * \overrightarrow{F}_{ext} \quad (2.11)$$

where $\overrightarrow{\tau}_{ext}$ are the torques applied to motors and $\overrightarrow{F}_{ext}$ are the cutting forces applied to the robot end-effector. Because joints have been approximated with torsional springs, the angular deformation of every joint can be calculated from Hooke's law as follows:

$$\tau = k * d\theta \rightarrow d\theta = \frac{\tau}{k} \quad (2.12)$$

where k is joint spring stiffness value of the joint in Nm/rad , while the minus sign has been omitted because for this model the deformation direction is defined from torque sign. After estimating all six angular deformations, the deformed cutting tool position can be calculated. Figure 2.6 summarizes the aforementioned procedure with a flowchart.

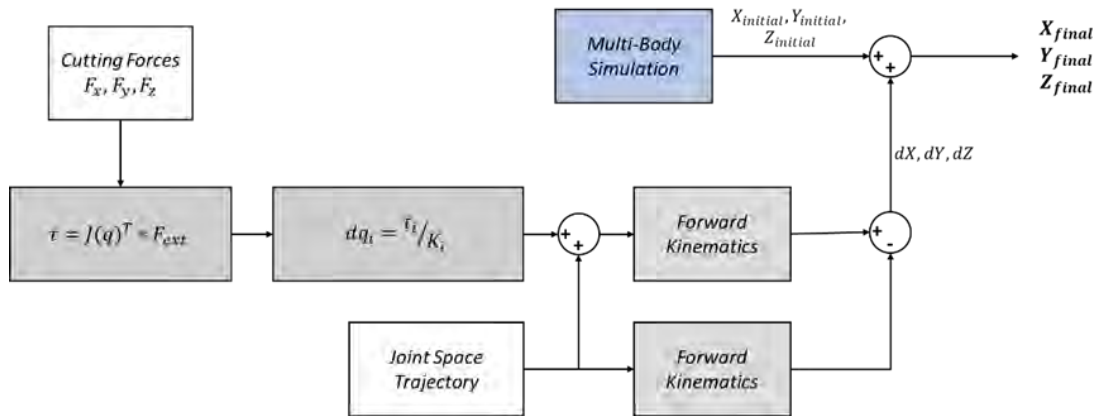


Figure 2.6 Calculation of the cutting tool deflections due to the compliance of the joints

2.3.2.3. Control Logic

Robotic systems combine mechanical, electrical, and software parts to perform the commanded functions; as a result, the controller architecture has a significant impact on the manipulator performance and the applications it can accomplish. A joint space controller has been developed to further extend the robot multi-body model and lead to a more realistic digital representation of the real robot. In addition, a PD controller for every joint has been included to create a closed-loop control system. The architecture of the proposed controller is presented in Figure 2.7 below.

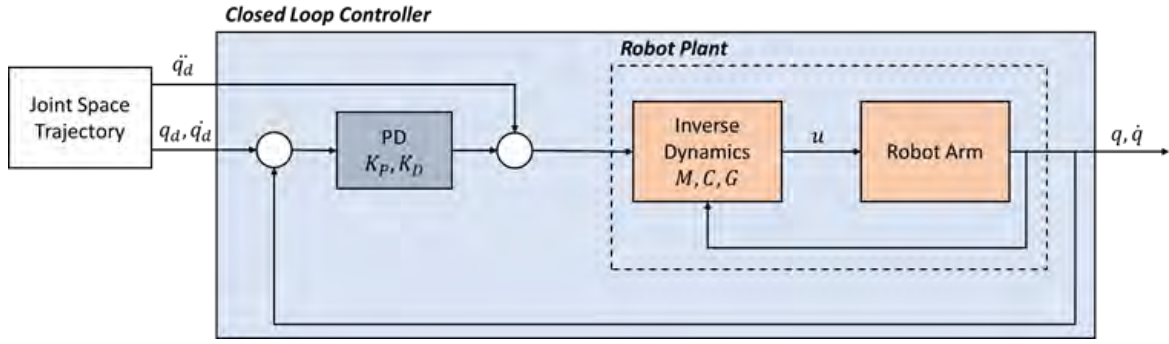


Figure 2.7 Proposed architecture for modelling of the controller

After taking into account the dynamics of an N non-fixed joints manipulator, the control torque vector can be expressed as follows:

$$\vec{u} = M(\vec{q})\ddot{\vec{q}} + C(\vec{q}, \dot{\vec{q}})\dot{\vec{q}} + G(\vec{q}) \quad (2.13)$$

where $M(\vec{q})$ is the joint space mass matrix of the robot, $C(\vec{q}, \dot{\vec{q}})\dot{\vec{q}}$ is the velocity product torque, and $G(\vec{q})$ is the gravity torque for the specific configuration. Furthermore, due to the PD controllers the above equation can be transformed into the following form:

$$\vec{u} = M(\vec{q})(\ddot{\vec{q}} - K_d\vec{\dot{q}}_e - K_p\vec{q}_e) + C(\vec{q}, \dot{\vec{q}})\dot{\vec{q}} + G(\vec{q}) \quad (2.14)$$

where $\vec{q}_e = \vec{q} - \vec{q}_d$ is the positional error, $\vec{\dot{q}}_e = \dot{\vec{q}} - \dot{\vec{q}}_d$ is the velocity error, and K_p, K_d are the diagonal matrices of proportional and derivative gains, respectively [2.48].

Tuning of the PD controller's parameters has been based on the requirement to achieve positional error in the order of micrometer, under no loaded motions. For a full description of the behavior of the robotic arm, the actual control algorithm of the robot should have been considered, also incorporating the dynamic response of the mechatronic system of the joints (drives, motors, etc.). However, it was not possible to acquire the knowledge of the actual control system parameters for the specific robot that has been modeled. As such, the minimization of the positional error at no-load motions enables accurately considering only the deflections introduced due to the machining process.

2.3.3. Model Implementation

In this work, a robotic machining cell has been utilized, which is comprised of a Yaskawa GP225, 6-DoF robotic arm and a Yaskawa DK-500 2-DoF rotary table. The existence of the rotary table provides two additional degrees of freedom and heavily increases the solution space of the workpiece placement optimization algorithm. In essence, it also enables consideration of pose-dependent stiffness, during workpiece placement, apart from position-dependent, which would be the limit

without these two extra degrees of freedom. Nevertheless, this will be explained in more detail in Section 2.6. The working volume of the machining cell considering the table and the robot is a cube of $500\text{mm} \times 500\text{mm} \times 500\text{mm}$, which is placed on the topmost surface of the table. The spindle is an HSD ES796, with a maximum power of 18 kW and a maximum rotational speed of 12000 RPM. The weight of the spindle is approximately 80kg. Figure 2.8 depicts the robot machining cell.

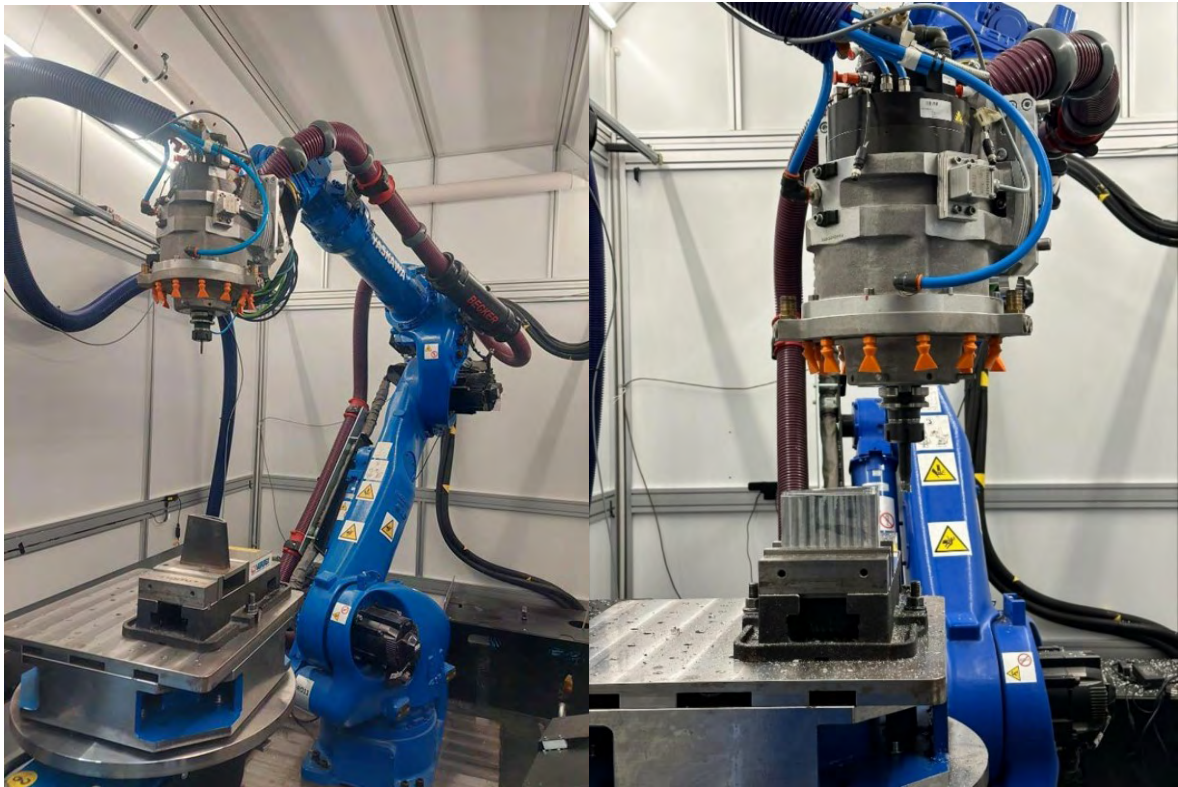


Figure 2.8 The robot machining cell used in this work

Software implementation of the model presented in this section has been performed in the Matlab (R2022b)-Simulink environment, in order to create a fully parametric model, applicable to any six-axis industrial robot. This model is an extension of a model presented in a previous work, which this author has been part of [2.6]. The complete implementation architecture of the MBS is presented in Figure 6 below.

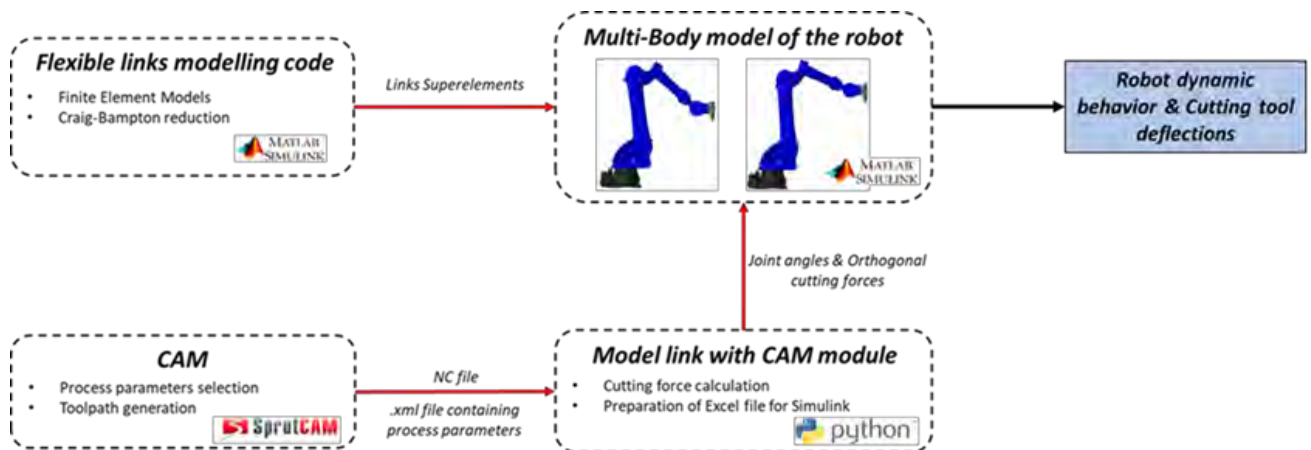


Figure 2.9 Implementation overview of the developed model [2.6]

Using the Simulink environment, it has been attempted to create an accurate digital representation of the robot structure by using different blocks for the dynamic behaviour representation of its main components. From Section 2.3.2, it is becoming clear that the joints and the links are the most significant components of the robot to model when its dynamic behaviour is examined; as a result, their modelling accuracy is of utmost importance for the MBS. The developed model requires as input the joint angles and the generated cutting forces and returns the predicted Cartesian position of the cutting tool throughout the process. Those values can be used later for the estimation of the cutting tool positional error during the process, when compared with the toolpath reference positions. The Simulink blocks used for the flexible link representation demand as input the 3D CAD file, the interface node coordinates, and the reduced order mass, stiffness, and damping matrices, or, in other words, the link Superelement. As for the joints' representative blocks, only the damping coefficient values are required, since the spring stiffness values are imported to the model through the process described in Section 2.3.2.

It is noted that due to a lack of experimental data for this specific Yaskawa robot, the values of Table 2.1 were obtained from a similar robot of the same manufacturer [2.38]. According to the literature, general-purpose robots with comparable reach and payload characteristics have similar joint stiffness and damping values [2.38], [2.49], [2.50]. The following approximations have also been done during the modeling process:

- The robot base and flange have been modeled as rigid bodies, due to their increased stiffness compared to the robot links.
- The cutting tool and tool holder have also been modeled as rigid bodies, as well as their interfaces.
- The joint motors have been modeled as point masses, due to lack of data regarding their actual geometry.

Table 2.1 Joint stiffness and damping values adopted for the implementation of the model [2.38], [2.49]

	Joint Stiffness [Nm/rad] $\times 10^6$	Joint Damping [$Nm \cdot s/rad$]
Joint 1	885.25	2371.92
Joint 2	1991.5	2918.17
Joint 3	1994.4	670.37
Joint 4	166.63	316.03
Joint 5	302.43	77.51
Joint 6	4.85	5.89

The robot joints torque controller has also been developed in the Simulink environment together with the multi-body model presented above, using the Simulink Robotics System Toolbox. For the estimation of the closed-loop PD controller parameters, the PID Tuner tool of Simulink has been used, according to the requirement mentioned in Section 2.3.2.

For the solution of the system of the system of nonlinear differential equations, the ODE23t solver is used in the Simulink environment. ODE23t is a variable-step, implicit, second-order accurate trapezoidal-rule solver designed for moderately stiff systems. The multi-body model of the machining robot exhibits moderate numerical stiffness, due to different physical phenomena, interacting at varying timescales. Robot motion takes place at a significantly larger timescale compared to robot dynamics, so high frequency elastic modes coming from the links flexibility coexist with the low-frequency robot motion. Additionally, joint stiffness and damping introduce stiff restoring forces, and the PD control increases the effective closed-loop stiffness. The ODE23t solver uses an implicit formulation to address numerical stiffness and ensure stability, and, unlike other stiff solvers, it does not introduce artificial numerical damping, making it particularly suitable for preserving accuracy when modelling the vibration amplitudes of the flexible links.

Regarding the computational demands of the model, in its current implementation it requires 9 minutes of wall clock time to simulate 1 minute of machining at a very fine resolution (Timestep = 0.003s) a typical personal laptop. With a larger timestep, this computational time could be further reduced.

2.4. Validation of the Multi-Body Model

Before utilizing the MBS for developing surrogate optimization approaches, the quantification of its accuracy should be performed. Experimental validation of the model is necessary to ensure its accuracy and reliability by comparing the model outputs with real-world data and should be

performed before the adoption of the model by any potential industrial users. To achieve this, side milling experiments were conducted for various sets of process parameters, with different cutting directions and robot configurations. The side milling experiments were always machining passes in a straight line. Each experiment number corresponds to a single machining pass performed with the process parameters described in Table 2.2. The selection of different cutting parameters (and thus different induced cutting forces) examines the linearity of the physical system, in response to the load variation. The model, implemented in Simulink, is inherently linear due to the use of the linear spring damper systems for the joints and the method of generating the stiffness and damping matrices of the members. Additionally, the inclusion of experiments with various cutting directions and robot configurations aims to verify the ability of the model to successfully predict the pose-dependent stiffness of the robot arm throughout the working space.

The material used in all experiments was Aluminum 7075-T651, while the cutting tool was a R390-016A16-11L indexable end mill from Sandvik Coromant with R390-11 T3 04E-NL H13A inserts from the same manufacturer. In order to evaluate the dependence of the robot dynamic behavior with the robot configuration, experiments were carried out with four different configurations:

- Robot Configuration 1: Motion of the robot along the robot y axis (angle $R_Z = 0$)
- Robot Configuration 2: Motion of the robot along the robot x axis (angle $R_Z = 0$)
- Robot Configuration 3: Motion of the robot along the y axis (angle $R_Z = -30^\circ$)
- Robot Configuration 4: Motion of the robot along the x axis with the table rotated -30° (angle $R_Z = 60^\circ$)

The aforementioned robot configurations are presented in Figure 2.10, while the cutting parameters for each of the 23 total milling experiments can be found in Table 2.2. All process parameters values (feed per tooth, cutting speed, axial and radial depths of cut) were selected based on the working parameters window provided by the cutting tool manufacturer. There was no specific design of experiments methodology (e.g., factorial, Taguchi) selected for the identification of process parameter combinations, as the point of these experimental tests was just to compare the results against the simulation and not do any further statistical analysis afterwards.

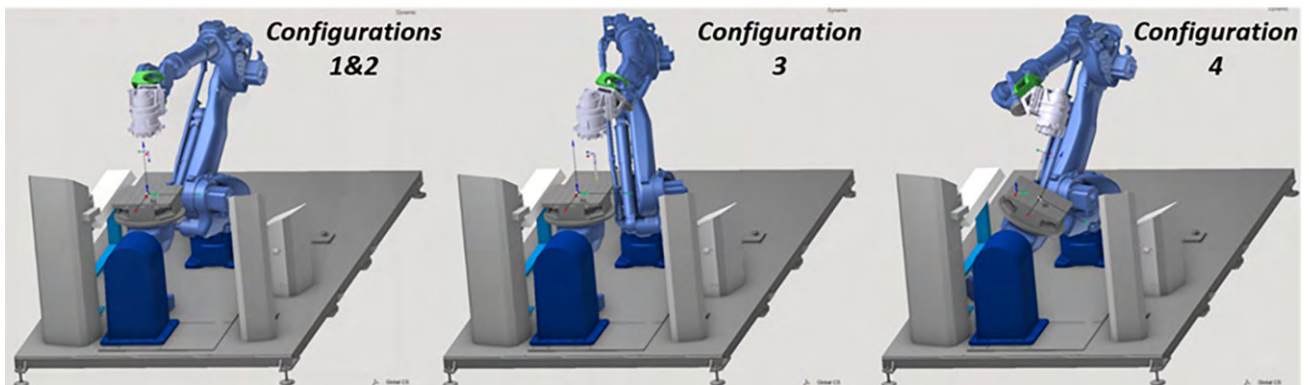


Figure 2.10 Robot configurations used for the validation experiments

Table 2.2 Cutting parameters for the model validation experiments

	Axial Depth of Cut [mm]	Radial Depth of Cut [mm]	Milling Mode	Robot Configuration
Setup 1	2	1	Climb	1
Setup 2	2	3	Climb	1
Setup 3	2	3	Conventional	1
Setup 4	2	5	Conventional	1
Setup 5	2	8	Conventional	1
Setup 6	2	14	Conventional	2
Setup 7	8	3	Conventional	2
Setup 8	8	3	Climb	2
Setup 9	2	1	Climb	3
Setup 10	2	8	Conventional	3
Setup 11	2	10	Climb	3
Setup 12	2	9	Conventional	3
Setup 13	4	6	Conventional	3
Setup 14	4	6	Climb	3
Setup 15	4	10	Conventional	3
Setup 16	4	14	Conventional	3
Setup 17	2	8	Conventional	4
Setup 18	2	10	Climb	4
Setup 19	2	9	Conventional	4
Setup 20	4	6	Conventional	4
Setup 21	4	6	Climb	4

Setup 22	4	10	Conventional	4
Setup 23	4	14	Conventional	4

It is noted that in addition to the process parameters mentioned in the table above, for all the experiments the feed per tooth was 0.09 mm and the spindle speed 11000 RPM.

At the end of every experiment, the dimensions of the machined workpiece were measured to the perpendicular direction of the feed (M1) and to the axial direction of the cutting tool (M2). Those measurements were used later in comparison with the positional error predicted by the MBS. The results of the comparison are presented in Table 2.3, as well as Figure 2.11 and Figure 2.12.

Table 2.3 Results of the model validation experiments

	<i>M1</i> Calculated [mm]	<i>M1</i> Measured [mm]	<i>M2</i> Calculated [mm]	<i>M2</i> Measured [mm]	<i>M1</i> Absolute Difference [mm]	<i>M2</i> Absolute Difference [mm]
Setup 1	-0.047	-0.050	0.020	0.000	0.003	0.020
Setup 2	-0.100	-0.10	-0.048	-0.050	0.000	0.002
Setup 3	0.150	0.050	-0.020	0.000	0.100	0.020
Setup 4	-0.230	-0.150	-0.015	-0.150	0.080	0.135
Setup 5	-0.340	-0.100	0.000	-0.150	0.240	0.150
Setup 6	-0.480	-0.100	-0.070	-0.100	0.380	0.030
Setup 7	-0.390	-0.200	0.200	0.000	0.190	0.200
Setup 8	0.600	0.400	0.060	0.300	0.200	0.240
Setup 9	-0.045	-0.050	0.030	0.000	0.005	0.030
Setup 10	0.112	0.200	-0.163	0.000	0.088	0.163
Setup 11	-0.176	-0.200	-0.010	-0.200	0.024	0.190
Setup 12	0.110	0.300	-0.170	0.000	0.190	0.170
Setup 13	0.220	0.200	-0.280	0.000	0.020	0.280
Setup 14	-0.300	-0.300	-0.120	-0.200	0.000	0.080

Setup 15	0.210	0.350	-0.350	-0.200	0.140	0.150
Setup 16	0.160	0.400	-0.310	0.000	0.240	0.310
Setup 17	0.120	0.050	-0.120	-0.250	0.070	0.130
Setup 18	0.050	0.500	-0.020	-0.200	0.450	0.180
Setup 19	-0.120	-0.500	0.130	0.300	0.380	0.170
Setup 20	0.210	0.250	-0.20	0.000	0.040	0.200
Setup 21	0.130	0.600	-0.030	-0.150	0.470	0.120
Setup 22	-0.250	-0.900	-0.290	-0.400	0.650	0.110
Setup 23	0.200	-1.100	-0.30	-0.900	1.300	0.600

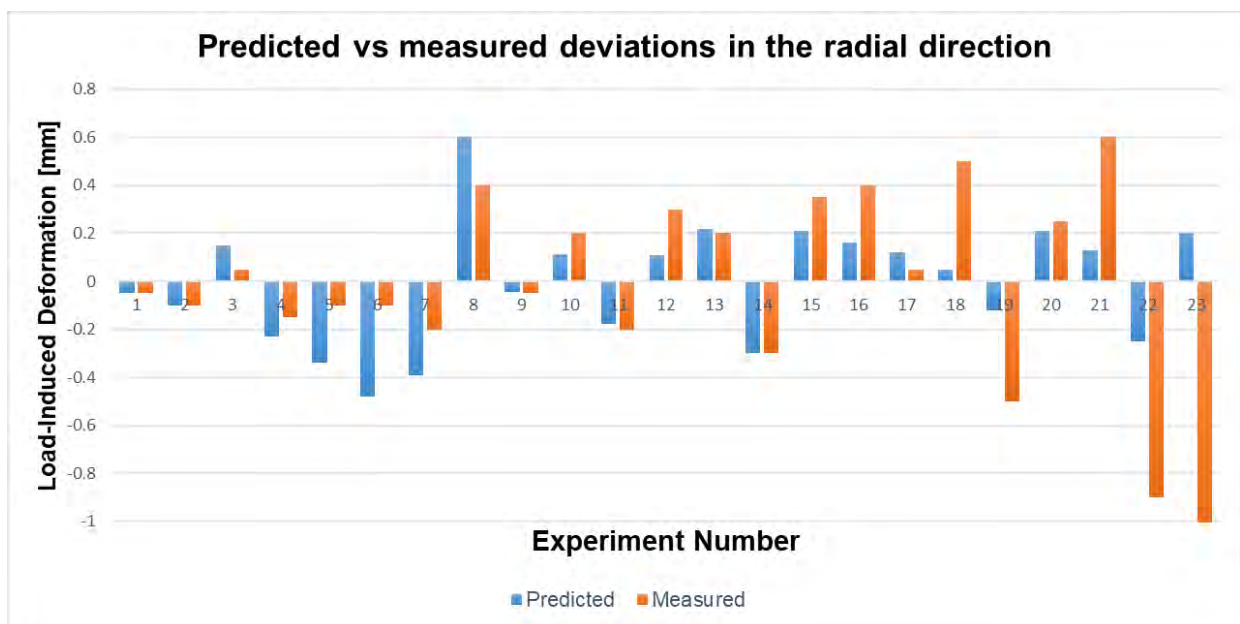


Figure 2.11 Predicted vs Measured deviations in the radial direction (M1)

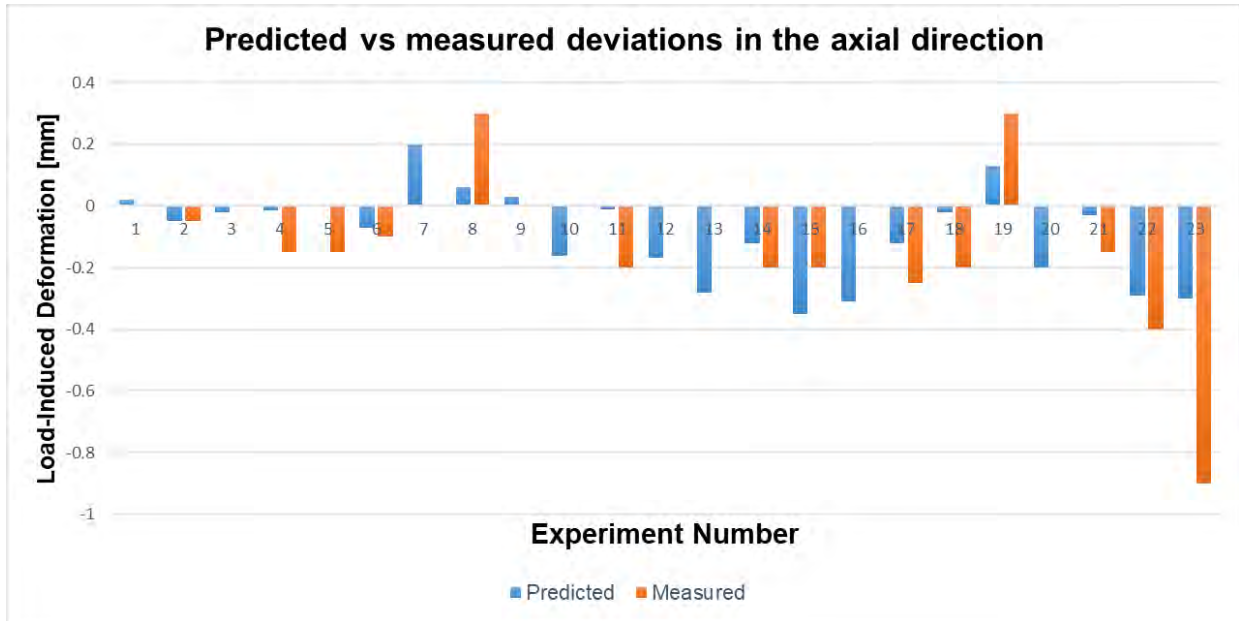


Figure 2.12 Predicted vs Measured deviations in the axial direction (M2)

It is evident that, with certain exceptions, the error predictions of the MBS have small deviations from the measured values. It is noted that during experiments 22 and 23 the effect of chatter was present during the machining process; therefore, the robot was in a resonant state. The linear approach of the MBS cannot simulate this situation with sufficient accuracy. The non-linearity of the robot vibrations when chatter takes place is something that is not yet accounted for in this model but is addressed with the developments of pillar 2 of this research, in-line during the milling process. The mean deviation between simulated and measured values is 13.7% for the radial direction and 10.8% for the axial direction. This result can be considered acceptable, considering the approximations and limitations of this specific MBS. Most importantly, it can verify that the MBS is able to be used as a basis for surrogate optimization of the robot machining process, which will be explained in detail in the next sections.

2.5. Stiffness maps generation

The ability to model the dynamic behaviour of the robot, provides an effective method to calculate its stiffness within its working envelope. However, in an optimization context, it is not practical to run a simulation within the optimization loop, each time a new configuration is tested. A very popular approach is to create surrogate, data-driven models based on synthetic datasets, generated from high-fidelity simulations [2.51]. This approach is followed in this work as well. The MBS enables to calculate the stiffness of the robot in different positions and postures. The cartesian stiffness of the robot (X, Y and Z axes in the Global Coordinate System of the robot) is calculated. A total of 6480 points are simulated in the $500mm \times 500mm \times 500mm$ working volume of the cell, at 30

different robot orientations. This forms the main input for the optimization approaches that will be described in the next sections.

Before moving on to the description of the optimization algorithms, it is also interesting to discuss the stiffness characteristics of the robotic arm, which can be visualized from the synthetic dataset in the form of stiffness maps. These stiffness maps depict the robot cartesian stiffness in a specific axis, at the XY plane (XY coordinates in the Global Coordinate System of the robot) for a specific “slice” of the working volume in the Z direction, with the robot in a specific configuration. The unit of stiffness in all figures is N/mm. Figure 2.13 represents the cartesian stiffness maps of a slice at $Z = 0\text{mm}$ (i.e. the topmost surface of the table), with the angle $R_Z = 40^\circ$ (R_Z , being the angle around the cutting tool axis – see Figure 2.16). Figure 2.14 represents the cartesian stiffness maps of a slice at $Z = 500\text{mm}$, with the angle $R_Z = 40^\circ$ and Figure 2.15 represents the cartesian stiffness maps of a slice at $Z = 0\text{mm}$, with the angle $R_Z = 80^\circ$.

The first observation is that the predicted stiffness mainly values fall in the expected range of 0.1-1N/ μm , according to literature [2.4]. An exception to that is the Z-axis stiffness at the $R_Z = 80^\circ$ configuration, which are one order of magnitude higher. This configuration exhibits a higher stiffness overall than all other configurations and the extreme difference compared to the other two can be attributed to the fact that as R_Z increases, the angle of the second link of the robot with the vertical axis is significantly reduced (Figure 2.17), which enables it to support the Z-axis loads in-plane, instead of transverse. Therefore, the available contribution of the second link towards the global stiffness increases significantly. The position dependence of the stiffness is also proven, by observing the figures, X and Y coordinates seem to have a higher influence than the Z coordinate. Additionally, it is also clear that the robot configuration can be optimized, using the redundant angle (R_Z), to heavily influence its stiffness. However, by observing the figures, one can notice that although the absolute stiffness is changing between different configurations, the distribution of the stiffness magnitude in the XY plane follows roughly the same trend. This means that the workpiece placement (which dictates position) and the pose optimization (which dictates configuration) can be decoupled and performed in discrete steps

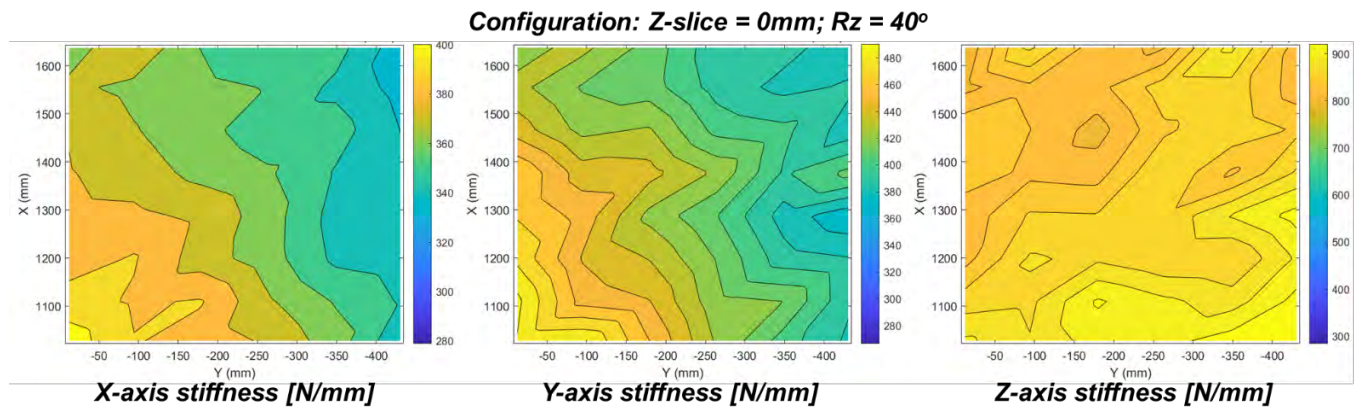


Figure 2.13 Stiffness maps at $Z = 0\text{mm}$ for $R_Z = 40^\circ$

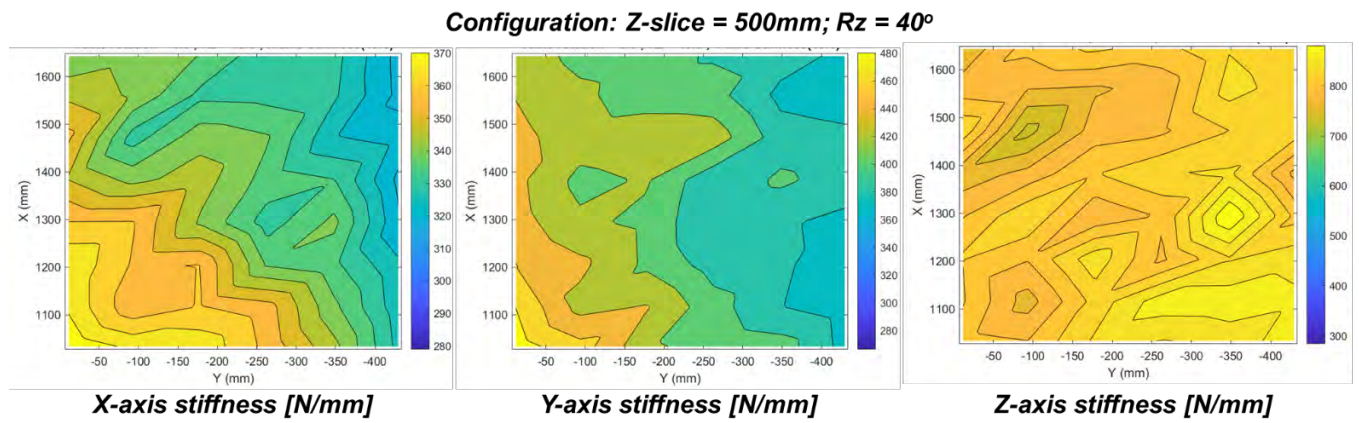
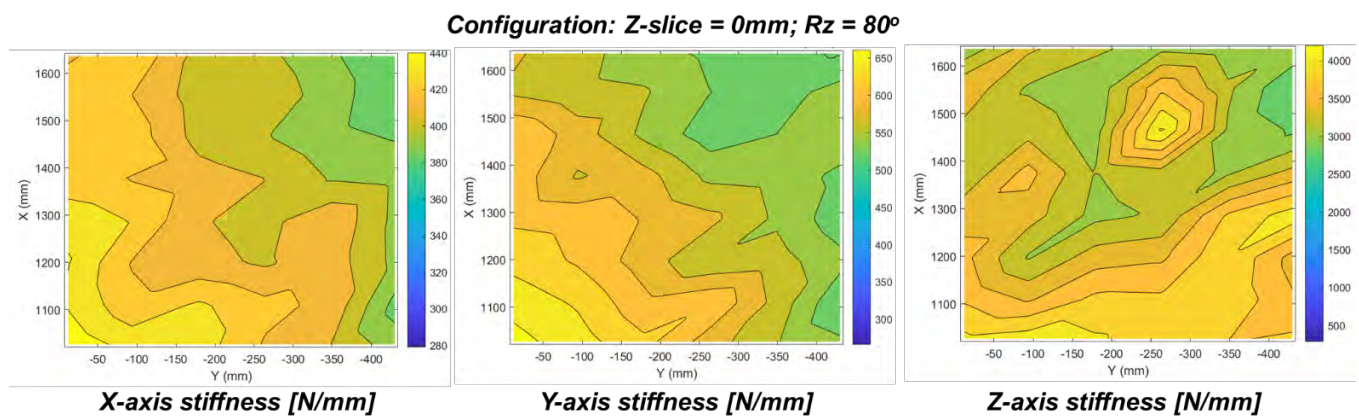
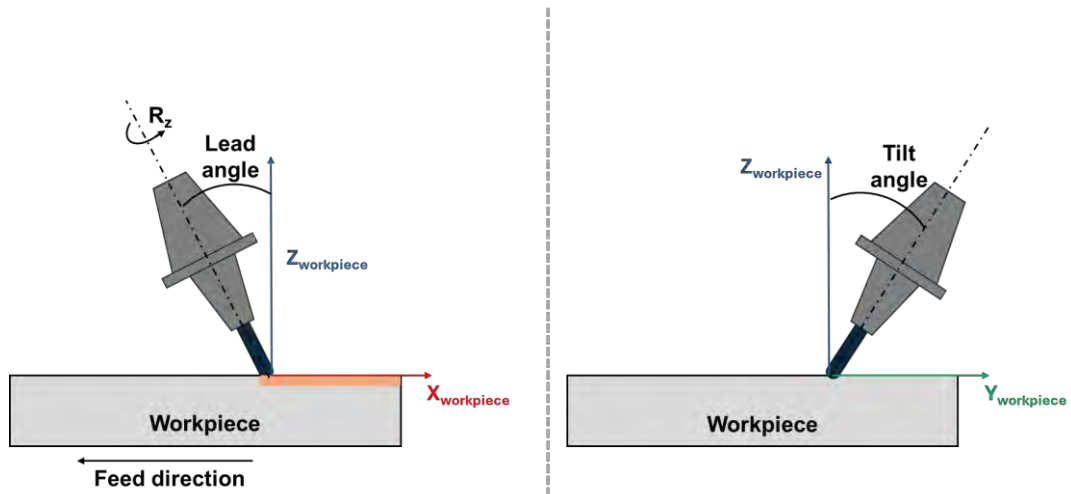
Figure 2.14 Stiffness maps for $Z = 500\text{mm}$ and $R_z = 40^\circ$ Figure 2.15 Stiffness maps at $Z = 0\text{mm}$ and $R_z = 80^\circ$ 

Figure 2.16 Geometry of 5-axis milling

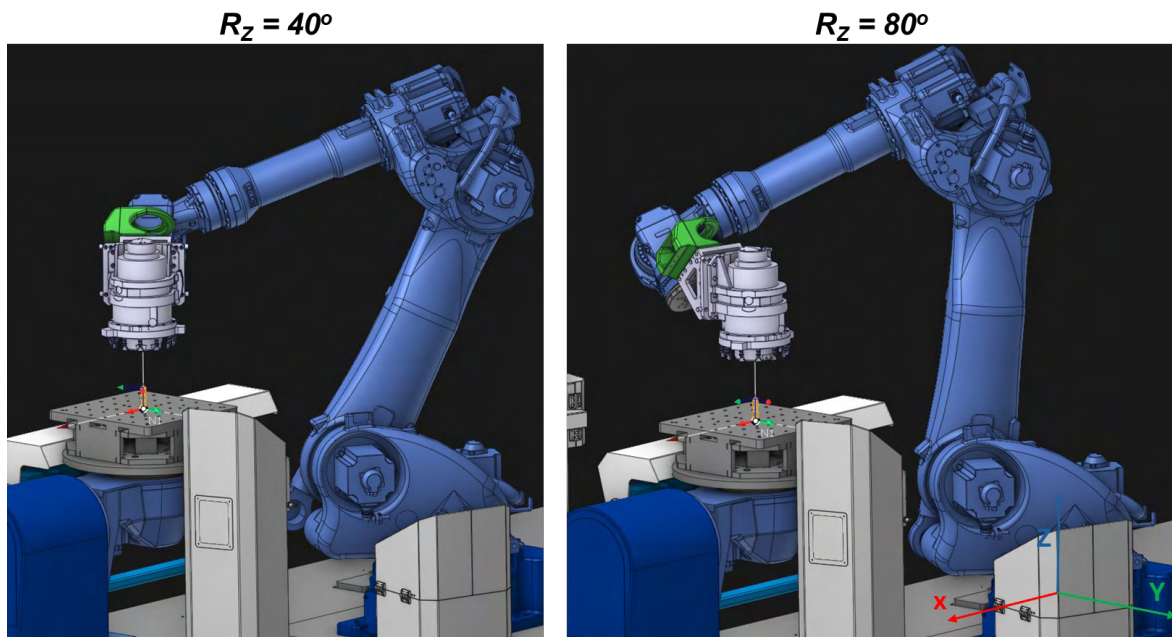


Figure 2.17 Pose of the robot at the center of the table for $R_z = 40^\circ$ (left) and $R_z = 80^\circ$ (right)

2.6. Workpiece Placement Optimization

2.6.1. Machining Feature Extraction

The first step in identifying the optimal placement for the workpiece is to understand the geometry of the features to be machined. As mentioned previously, one of the main goals of this work is to develop the optimization tools in such a way that they can be integrated in the typical existing workflow of a process planner for machining operations. The selection of the workpiece position and orientation is usually the first step during process planning, before toolpath generation. This means that the only source of information regarding the part geometry is the CAD file of the part. Extraction of machining features from the CAD file is a task that is being discussed in research for some time and there are different approaches that can be followed. The main differences can be observed in the filetype that is used as input (STEP or STL) and the way the features are extracted (fully automated or semi-automated) [2.52].

Usually, STEP is the preferred file format to utilize for extraction of geometric features as it holds both geometrical and topological information, as well as the relationships between adjacent surfaces [2.53]. As such, the STEP file format is also used in this work to process the geometrical information of the CAD file. Regarding the selection between fully automated feature extraction or semi-automated, in this study, the semi-automated approach has been favored. There are two main reasons behind this selection. Firstly, the fully automated approaches are still not robust enough to generalize to every possible geometry and are especially effective in detecting primitive geometries.

On the other hand, when complex, freeform surfaces are considered, the fully automated methods tend to face some limitations [2.54]. Advancing feature recognition techniques is not in the main scope of this work, while having a universally robust approach is of paramount importance, since industrial viability is a major pillar of the work. Secondly, having a semi-automated approach where the user selects surfaces that comprise a machining feature is the typical procedure followed by machining process planners, when they use a CAM software (especially for finishing operations). So, this approach does not disrupt the current workflow, if the user interface is designed in such a way to resemble a CAM software.

To achieve this, the feature extraction module is implemented in Python, utilizing the `pythonocc` package [2.55], which is based on the well-known Open Cascade kernel. The module launches a 3D viewer, where the user can import a CAD file in a STEP format. Then, machining features can be defined by clicking on the surfaces that comprise them, in a similar fashion to machining feature definition in CAM software. Internally within the module, a feature is described as a set of shapes (faces) that constitute a compound. Utilizing the internal functions of Open Cascade, a bounding box can be calculated for the compound, represented by the minimum and maximum values in the X, Y and Z coordinates. This bounding box is used as a reference for each feature, during the workpiece placement phase.

Next, the dominant machining direction is computed, obtained as the normalized average of the surface normal of the faces that comprise the feature. While the main function of the bounding box is to aid in definition of workpiece position, the dominant machining direction is aiding in the definition of workpiece orientation. Generally, it is preferred to align the normal vector of the surface with the stiffer direction of the robot, since this will affect the dimensional accuracy of the end part [2.56]. Within the module, each of the faces that comprises the feature is parametrized as a boundary representation (BREP) surface, utilizing the internal functions of Open Cascade. After is is parametrized, it can be expressed as a function of two variables, called parameters of the surface, $r(u, v)$ (Figure 2.18). Utilizing the internal functions of Open Cascade, the partial derivatives at the mid-point of the surface are determined numerically. Then, the surface normal vector can be calculated as follows:

$$n = \frac{\partial r}{\partial u} \times \frac{\partial r}{\partial v} \quad (2.15)$$

The dominant machining direction of the feature is obtained as the normalized average of the surface normal of the feature faces:

$$d_i = \frac{1}{A_{total,i}} \sum_j A_{ij} \cdot n_{ij} \quad (2.16)$$

where:

- n_{ij} is the surface normal of face j in feature i .
- A_{ij} is the surface area of face j in feature i
- A_{total} is the total surface area of all faces in feature i .

In cases of symmetric features, a null vector is returned, so that it can be taken into account into workpiece placement optimization and omit orientation optimization for this specific feature.

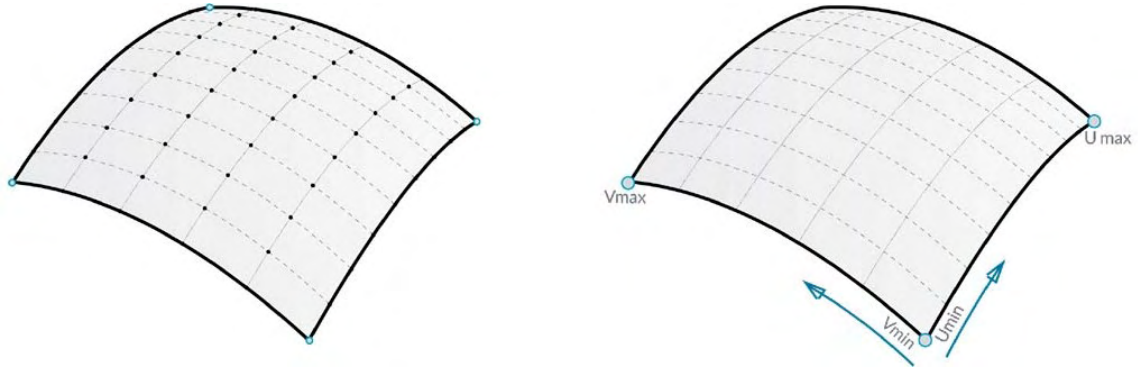


Figure 2.18 Typical parametrization of a surface using u and v variables [2.57]

When the bounding box and normal vectors of the feature are calculated, they can also be visualized in the 3D viewer. When the user has defined all the machining features, the next phase (workpiece placement optimization) can begin.

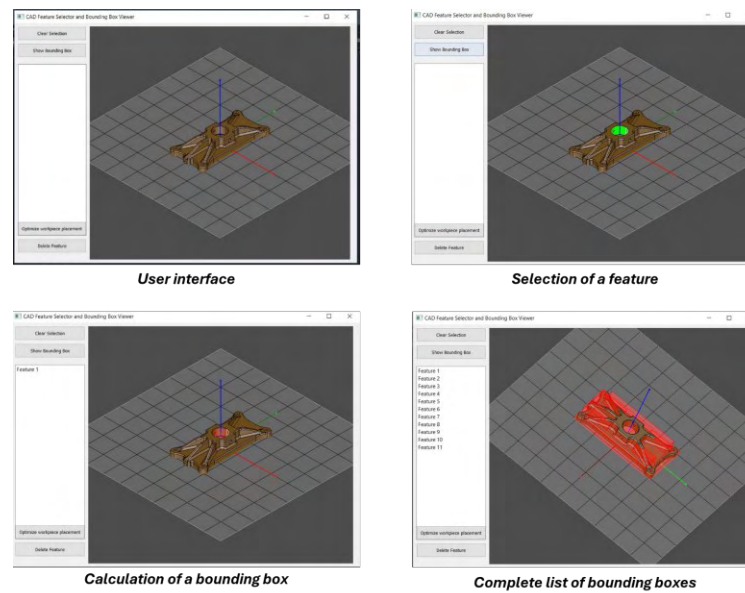


Figure 2.19 Overview of the machining feature extraction module

2.6.2. Workpiece Placement Algorithm

The starting point of the workpiece placement algorithm is the regularization of the stiffness values that have been calculated from the MBS, into stiffness grids, dependent on the tilt angle of the rotary

table (angle around the X-axis of the robot, as shown in Figure 2.17). During the generation of the synthetic dataset, stiffness simulations have been performed for three different tilt angles of the table (-30° , 0° and 20°), testing multiple R_z configurations in each tilt angle. For the creation of the tilt angle dependent stiffness grids, the stiffness values of $R_z = 0^\circ$ are preserved for each of the different tilt angle values.

For each of the different tilt angle values, a uniform voxel grid is created. Each voxel is described by the coordinates of each center point (X, Y, Z in the local, rotating coordinate system of the rotary table) and the stiffness vector. The stiffness vector of each voxel is calculated, based on the stiffness values obtained from the MBS. The stiffness vector S is comprised of three components $S = [S_x, S_y, S_z]$, where S_i is the stiffness in the cartesian axis i of the global coordinate system of the robot, which is calculated from the Multi-Body Simulation, as explained in section 2.3. Linear interpolation is performed, in cases where the voxel center point does not coincide with an existing point from the simulation. Due to the density of the original points generated from the MBS, linear interpolation is considered to be sufficient for this specific application. The voxel grid is parametric in terms of voxel size and allows the potential user to either select from the default value, which is equal to the original spacing of the simulation points in the MBS (100mm), or a user-defined value. This depends on the feature sizes – and the bounding boxes sizes respectively – that dictate the necessary resolution on the voxel grid. Figure 2.20 depicts the way the voxel grid describes the robot stiffness within the combined workspace of the robot and rotary table. In this specific case, the voxel grid for a tilt angle of 0° is depicted.

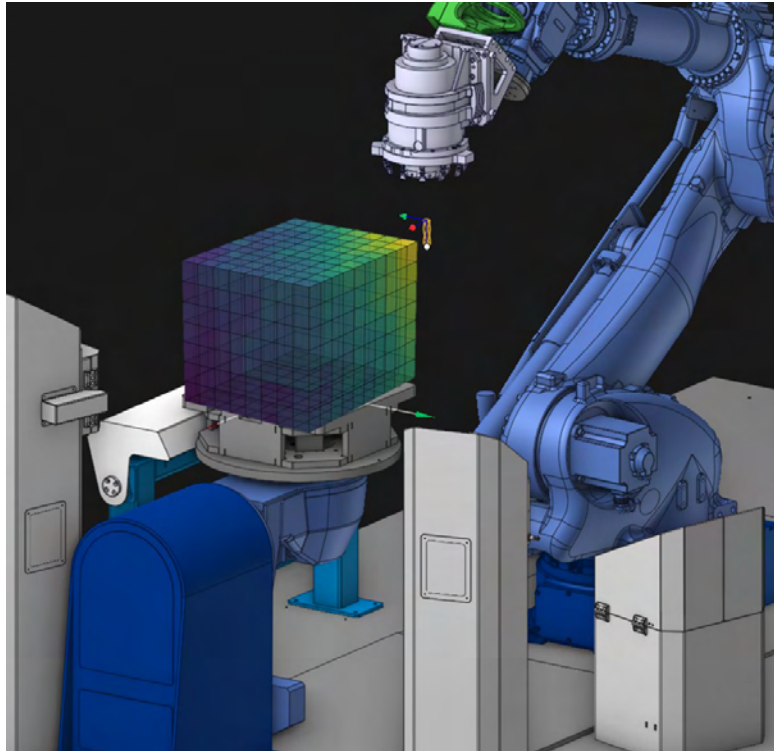


Figure 2.20 The workspace of the cell defined as a stiffness voxel grid

Finally, the workpiece placement can take place. First, a scan region $W \subset \mathbb{R}^3$ is defined, where the workpiece may be placed. By default, this is equal to the combined workspace of the robot and rotary table, but can be modified by the user, if necessary, to apply specific restrictions. Different candidate placements are generated in this scan region. Each candidate placement is defined as an offset of the geometric center of the component to be machined. For each candidate placement origin $o \in W$, it is confirmed if the translated bounding box of the whole component lies within the bounds of the combined workspace of the robot and rotary table. If not, the candidate placement is discarded. For each of the valid placements, a stiffness score is calculated for all possible rotations of the table around the X or Z-axis of the robot. Since each feature can be machined at a different table orientation without any loss of accuracy (the machining setup does not change), it is reasonable to score a feature in a given placement, based on the best possible orientation it can assume. For the calculation of the stiffness score of each feature, the voxels that lie within the bounding box of the feature (even partially) are taken into account. The average of the stiffness vectors of the voxels that lie within the bounding box is calculated and then the dot product of the sum with the vector of the dominant machining direction is calculated, to also preserve the alignment of the surface normal with the stiffest direction. In cases of symmetrical features, the average of the stiffness vectors is multiplied with the unit vector. The score of each valid placement can be calculated as follows:

$$score(o) = \sum_i^{N_{features}} \operatorname{argmax}(d \cdot \bar{S}_i(o, \theta, \varphi)) \quad (2.17)$$

where:

$$d = \begin{cases} [1,1,1], & \text{if the feature is symmetrical} \\ d_i = \frac{1}{A_{total,i}} \sum_j A_{ij} \cdot n_{ij}, & \text{else} \end{cases} \quad (2.18)$$

$$\bar{S}(o, \theta, \varphi) = \frac{1}{N_{voxels}} \sum_k^{N_{voxels}} s(o, \theta, \varphi) \quad (2.19)$$

where:

- $s(o, \theta, \varphi)$ is the stiffness vector at a specific placement, for a specific rotation of the table around the X-axis (θ) and a specific rotation of the table around the Z-axis (φ)
- N_{voxels} the voxels that lie, even partially, within the bounding box of the feature

Based on the maximum score, the optimal placement is calculated. The optimal placement is the global placement for the entire machining process of the workpiece, considering the contribution of all features, since the machining setup should not be changed between different features, as this is

a potential source of error. Then, each feature can be machined with a different table orientation, with the given optimal placement, as this does not affect the machining setup. The final step is to calculate the optimal orientation of the workpiece (angles θ and φ) for the optimal placement. In the end, the results are shown to the user, so that they can be used as input in the CAM software during process planning. Figure 2.21 depicts a flowchart of the workpiece placement optimization algorithm. Also, the pseudocode of the two algorithms (Algorithm 2.1 and Algorithm 2.2) can assist the reader in further understanding the working principles of the workpiece placement optimization.

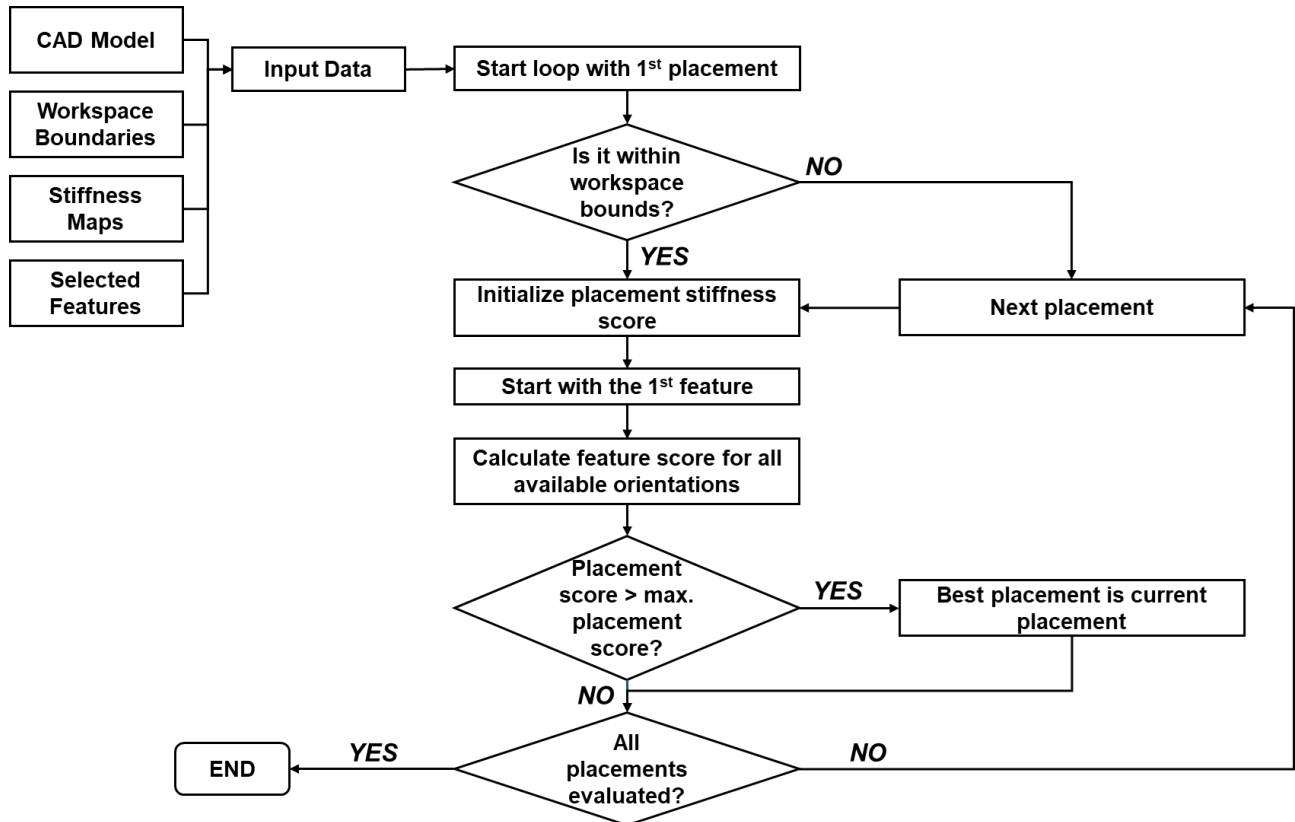


Figure 2.21 Flowchart of the workpiece placement optimization algorithm

Algorithm 2.1 Pseudo code of the CAD processing algorithm

Input: CAD Model

Output: Optimal placement, Optimal θ and φ angles for each feature

```

1:  load STEP_model from file
2:  initialize 3D viewer with STEP_model
3:  selected_features  $\leftarrow$  GetUserSelectedFaces(STEP_model)
4:  workspace_limits  $\leftarrow$  DefineWorkspaceBounds()
5:  stiffness_maps  $\leftarrow$  LoadDirectionalStiffnessData(tilt_angles)
6:  for feature  $\in$  selected_features
7:      for face  $\in$  feature_faces
8:          n_i  $\leftarrow$  UnitNormal(face)
9:          A_i  $\leftarrow$  SurfaceArea(face)
10:         weighted_normal  $+= A_i * n_i$ 
11:         total_area  $+= A_i$ 
12:         avg_normal = weighted_normal/total_area
13:         bounding_box  $\leftarrow$  ComputeBoundingBox(selected_faces)
14:     end
15: end
16: optimal_position, optimal_theta, optimal_phi  $\leftarrow$  OptimizePlacement(selected_features, stiffness_maps,
    workspace_limits)
17: return optimal_position, optimal_theta, optimal_phi
18: close 3D viewer
19: end

```

Algorithm 2.2 Pseudo code of workpiece placement algorithm

Input: Selected features, bounding boxes of selected features, dominant machining directions of selected features, stiffness maps dependent on tilt angle, workspace limits

Output: Optimal placement, Optimal θ and φ angles for each feature

```

1:  Method OptimizePlacement
2:      candidate_positions  $\leftarrow$  VoxelizeGrid(workspace_limits)
3:      best_stiffness  $\leftarrow -\infty$ 
4:      best_position  $\leftarrow$  None
5:      for position  $\in$  candidate_positions
6:          if not FitsInWorkspace(position, bounding_box, workspace_limits)
7:              continue
8:          end
9:          for feature  $\in$  selected_features
10:             best_score  $\leftarrow$  0
11:             for  $\theta \in \{-30, 0, 20\}$ 
12:                 stiffness_map  $\leftarrow$  stiffness_maps[ $\theta$ ]
13:                 for  $\varphi \in \{-180 \dots 180\}$ 
14:                     K_local  $\leftarrow$  InterpolateStiffnessTensor(stiffness_map, p)
15:                     directional_stiffness  $\leftarrow$  K_local  $\cdot$  avg_normal
16:                     if directional_stiffness > best_score
17:                         best_score  $\leftarrow$  directional_stiffness
18:                     end
19:                 end
20:             end
21:             if best_score > best_stiffness
22:                 best_stiffness  $\leftarrow$  best_score
23:                 best_position  $\leftarrow$  position
24:             end
25:         end
26:     for feature  $\in$  selected_features
27:         best_theta  $\leftarrow$  None
28:         best_phi  $\leftarrow$  None
29:         best_score  $\leftarrow$  0
30:         for  $\theta \in \{-30, 0, 20\}$ 
31:             stiffness_map  $\leftarrow$  stiffness_maps[ $\theta$ ]
32:             for  $\varphi \in \{-180 \dots 180\}$ 
33:                 K_local  $\leftarrow$  InterpolateStiffnessTensor(stiffness_map, p)
34:                 directional_stiffness  $\leftarrow$  K_local  $\cdot$  avg_normal
35:                 if directional_stiffness > best_score
36:                     best_score  $\leftarrow$  directional_stiffness
37:                     best_theta  $\leftarrow$   $\theta$ 
38:                     best_phi  $\leftarrow$   $\varphi$ 
39:                 end
40:             end
41:         end
42:     end
43:     return best_position, best_theta, best_phi
44: end Method

```

2.7. Robot Posture Optimization

2.7.1. Neural Network Training based on Synthetic Data

In order to be able to execute the posture optimization, it is necessary to have a tool to calculate the stiffness of the robot at any arbitrary configuration (TCP position and orientation). To address this, a fully connected, feedforward neural network was trained, using the synthetic dataset described previously. The input dataset consists of the three cartesian stiffness values (X, Y and Z-axis in the Global Coordinate System of the robot) and the corresponding vector of the joint angles. The use of neural networks for this purpose assists in effectively capturing the non-linear relationship between the position and orientation of the TCP and the stiffness of the robot, which has been demonstrated in Section 2.5. The choice of the simple, feedforward neural network lies in the fact that low training and execution time are important, given that the accuracy is not compromised. Especially execution time is critical, since the network needs to make several predictions in each optimization loop. The network was implemented using the PyTorch package [2.58], which is one of the most widely known packages in Python for Artificial Intelligence development, implementing also tensors in its architecture, which significantly improve the training and execution speeds. The dataset has been split for training, testing and validation in an 80%-15%-5% ratio respectively. In the input layer, sinusoidal encoding was applied on the joint angle vector, with a single frequency (equation 2.20). Shuffling of the dataset between epochs was applied. Dropout rate and weight decay were not applied. The rest of the details of the neural network are presented in Table 2.4.

$$\text{Input Vector} = [\sin(q_i), \cos(q_i)], \quad i = 1 \dots 6 \quad (2.20)$$

Table 2.4 Details of the fully connected neural network

Fully Connected Neural Network Architecture	
Input layer	Joint angles after sinusoidal encoding - 12 neurons
Output layer	Cartesian stiffness (X, Y, Z) – 3 neurons
Number of hidden layers	4
Number of neurons per hidden layer	[128,128,128,128]
Activation function	Gaussian Error Linear Unit
Output type	Scalar
Training parameters	

Loss function	Mean Absolute Percentage Error (MAPE)
Optimization function	Adaptive Moment Estimation (ADAM)
Learning rate	0.001
Number of training epochs	300

The performance of the network is presented in Table 2.5. The values of R^2 and MAPE showcase a very good regression performance, which can be considered acceptable for the intended application of this work. Given the significantly increased complexity of more advanced architectures (e.g. Convolutional Neural Networks), there is no significant benefit in adopting them. It is also interesting to note that the cosine similarity is equal to 1, which means that the network captures perfectly the direction of the stiffness vector (i.e. the proportions between X, Y and Z-axis stiffness). Figure 2.22, Figure 2.23 and Figure 2.24 depict the evolution of R^2 , MAPE and cosine similarity over the training epochs, respectively. It can be observed that R^2 stabilizes after the longest interval of training time, requiring over 250 epochs, while MAPE and cosine similarity reach their optima very soon, close to 50 epochs.

Table 2.5 Evaluation metrics for the performance of the neural network

R^2	93.0%
MAPE	2.1%
Cosine Similarity	1.0

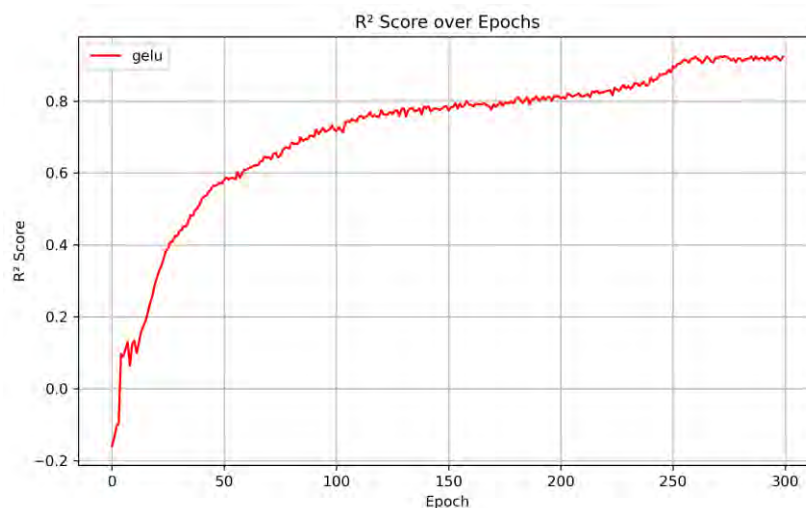


Figure 2.22 Evolution of R^2 over the training epochs

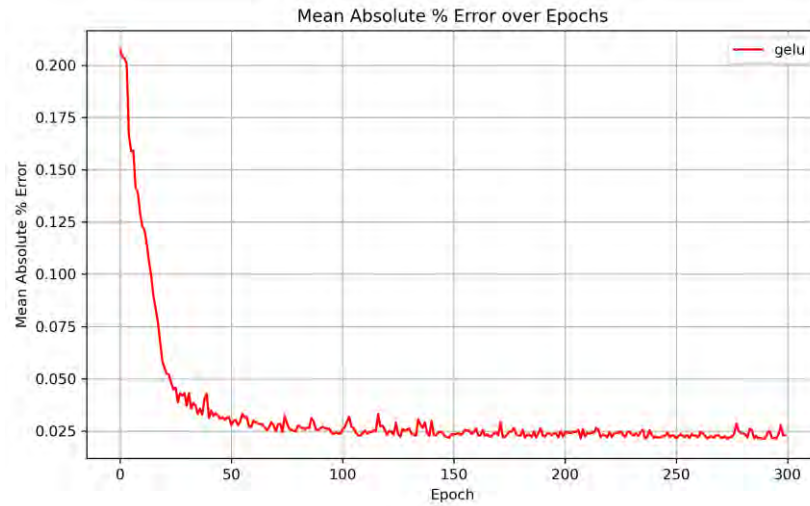


Figure 2.23 Evolution of MAPE over the training epochs

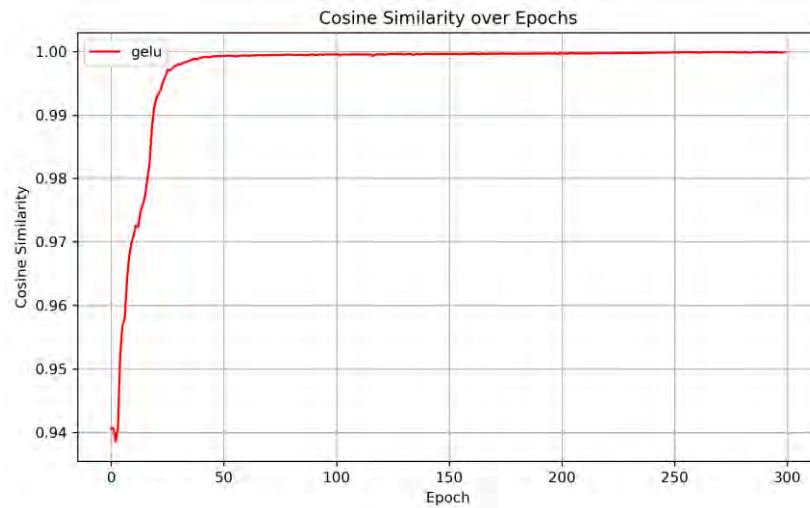


Figure 2.24 Evolution of the cosine similarity over the training epochs

2.7.2. Stiffness Performance Evaluation

The neural network predicts the stiffness of the robot in the three orthogonal axes of the Global Coordinate System of the robot. However, a singular value is required to be plugged into the optimization function. To this end, the stiffness ellipsoid of the robot is calculated and its volume is used as the stiffness metric, being a scalar value. The stiffness ellipsoid is attached at the TCP of the robot, as shown in Figure 2.25, and its principal axes have the direction and magnitude of the components of the stiffness vector, as they are calculated by the neural network. The volume of the stiffness ellipsoid can be calculated as follows.

$$v_{\text{ellipsoid}} = \frac{4}{3}\pi(|s_x s_y s_z|) \quad (2.21)$$

where s_x, s_y, s_z is the stiffness in the X, Y and Z-axis respectively.

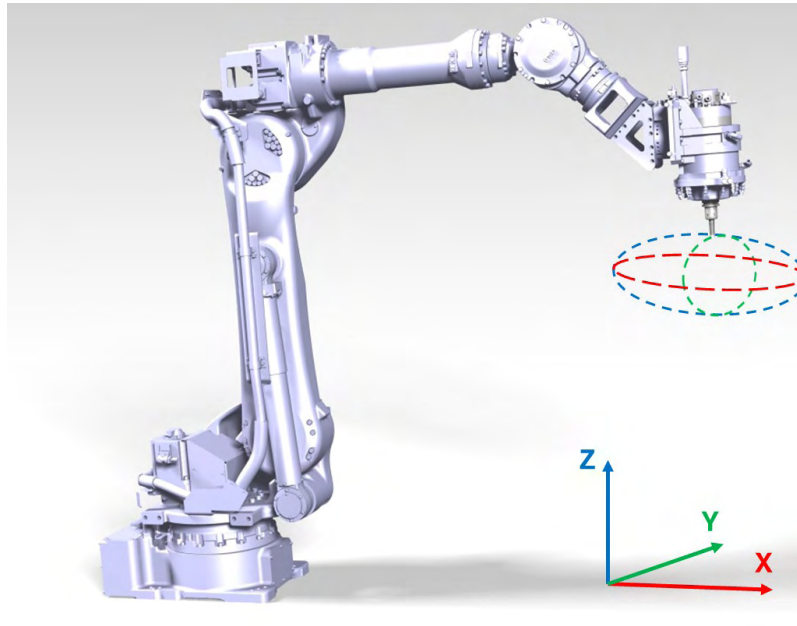


Figure 2.25 The stiffness ellipsoid

2.7.3. Kinematic Performance Evaluation

As mentioned previously in the manuscript, considering only the stiffness of the robot in the optimization of the redundant angle does not suffice. There is a chance that an optimal solution in terms of stiffness directs the robot toward a problematic area of its working envelope. The notion “problematic” can be defined as an area close to singularity or an area where high joint velocities and/or acceleration will be required to solve the inverse kinematic problem, as it is defined by the R_z dictated by the optimization and machining toolpath. It is obvious that traversing the robot through a singularity within the toolpath is detrimental for the machining performance. Additionally, having large joint velocities and accelerations can lead to vibrations at the TCP and/or kinematic errors. In such a case, the goal of the optimization is undermined.

To address this, the condition number of the Jacobian matrix of the robot is evaluated. The Jacobian matrix ($J(q)$) maps the relationship between joint velocities ($\dot{q}$) and end effector velocity ($\dot{X}$). This mapping can be calculated as follows, for a 6-DoF robotic arm:

$$\dot{X} = J(q)\dot{q} \quad (2.22)$$

where $\dot{X} = [\dot{x} \ \dot{y} \ \dot{z} \ \dot{\alpha} \ \dot{\beta} \ \dot{\gamma}]$

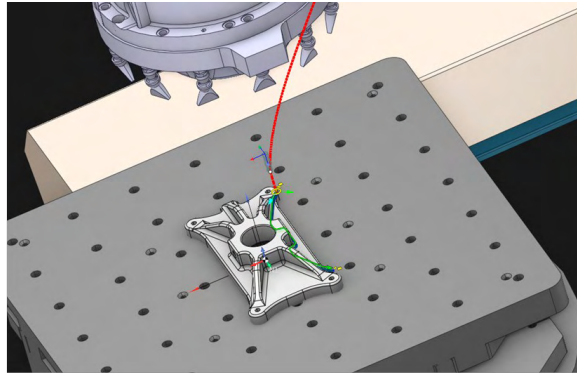
The condition number of a matrix A, denoted as κ can be defined as follows:

$$\|A\|_F = \sqrt{\sum_{i=1}^n \sum_{j=1}^n a_{ij}^2} = \sqrt{\text{trace}[A^T A]} \quad (2.23)$$

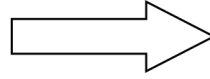
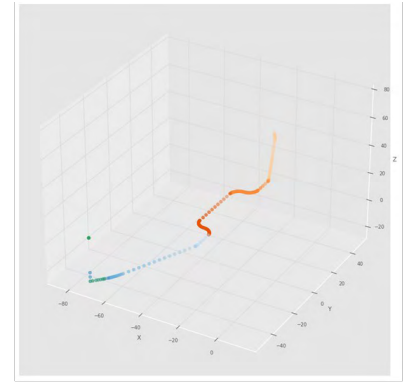
The condition number of a matrix measures how well-conditioned this matrix is. Essentially, it provides a measure how of much a perturbation in the input, affects the magnitude of the output. In the context of robotics, a low condition number of the Jacobian matrix implies that small joint movements produce proportionally small, stable end-effector movements in all directions. In contrast, a high condition number of the Jacobian matrix implies that the system is near a singularity, where some directions cartesian space may require large joint motions, or the robot may lose degrees of freedom. It is clear that the goal is to minimize the condition number to ensure good kinematic performance of the robot.

2.7.4. Optimization Function

The final step to achieve the optimal posture within the toolpath is to solve the multi-objective optimization function that aims to maximize the volume of the stiffness ellipsoid, while minimizing the condition number. Before solving the optimization problem for a given toolpath, a segmentation of the toolpath is performed. The segmentation takes place to enforce smoothness in the optimization of the toolpath. Calculating the optimal stiffness point-by-point might lead to large variations of R_z between consecutive points, which might again lead to larger than necessary joint velocities and accelerations, with the negative impact on the process that has been explained above. The segmentation of the toolpath is performed based on the radius of curvature of each point (calculated, using a rolling window of 5 points) and the normal vector. The radius of curvature segments the linear from the curved components and then the normal vector is used as a fallback mechanism in cases where a sharp turn takes place without any corner radius. In such a case, the two consecutive linear segments would not be segmented if the radius of curvature method was solely employed. Figure 2.26 depicts the segmentation of a typical contouring toolpath, based on the method described above.



Toolpath generated in SprutCAM for contouring a feature



Segmentation for piecewise optimization of toolpath

Figure 2.26 Toolpath segmentation based on the curvature and normal vector method

The optimization takes place at each segment, which means that the goal is to find a common optimal value of R_Z for the whole segment. The optimization function that is solved is the following:

$$\begin{aligned}
 & \text{Maximize} \\
 & w_1 v_{\text{ellipsoid}, \text{norm}} + w_2 \frac{1}{\kappa_{\text{norm}}} \\
 & \text{Such that} \\
 & q_{i, \min} \leq q_i \leq q_{i, \max} \\
 & R_{Z, \text{currentsegment}} - R_{Z, \text{previoussegment}} \leq 15^\circ
 \end{aligned} \tag{2.24}$$

where:

- w_1 and w_2 are weights that can be configured by the user based on the current situation, when machining a specific feature. For example, in a case of a roughing process, the user could set $w_1 = 0$, since machining errors are not that critical in this stage, but benefit from the optimization algorithm, by selecting the best posture for kinematic performance and enabling potentially higher feed rates. As a default value $w_1 = w_2 = 0.5$
- The subscript *norm* means that the ellipsoid volume and condition number are normalized. When optimizing a segment, the values of $v_{\text{ellipsoid}}$ and κ are calculated first for every point in the segment. Then, when solving the objective function for a specific point, the normalized values are used, dividing the value of the current segment point with the maximum value for the segment, for each of the two quantities. This is done, since there can be significant differences in the magnitudes of the two quantities, so using the raw values would introduce bias in the solution
- q_i denotes the angle of the i -th joint
- The limit of a maximum 15° variation between consecutive segments is enforced as an additional means to preserve toolpath smoothness

The pose optimization module is implemented in Python, utilizing the Robotics Toolbox for Python [2.59]. This simplifies the definition of the kinematics of the robotic arm within Python, which can be easily performed through a .URDF file that can be exported from Simscape MultiBody, where the MBS has been setup. The .URDF file can be also customized to enforce additional limitations to the allowable angles that the joints can reach. The toolpath is obtained automatically from the CAM software (SprutCAM), using the same custom-built post-processor, which was used to generate the input file for Simulink. Since this file is in a standardized format (.xlsx), it can be easily parsed in Python as well. After the posture of the robot is optimized, the part program for the Yaskawa robot (.JBI file) is automatically generated and can be directly imported into the robot controller to execute the machining task.

Figure 2.27 depicts a flowchart of the posture optimization algorithm. Also, the pseudocode of the algorithm (Algorithm 2.3), can assist the reader in further understanding the working principles of the workpiece placement optimization.

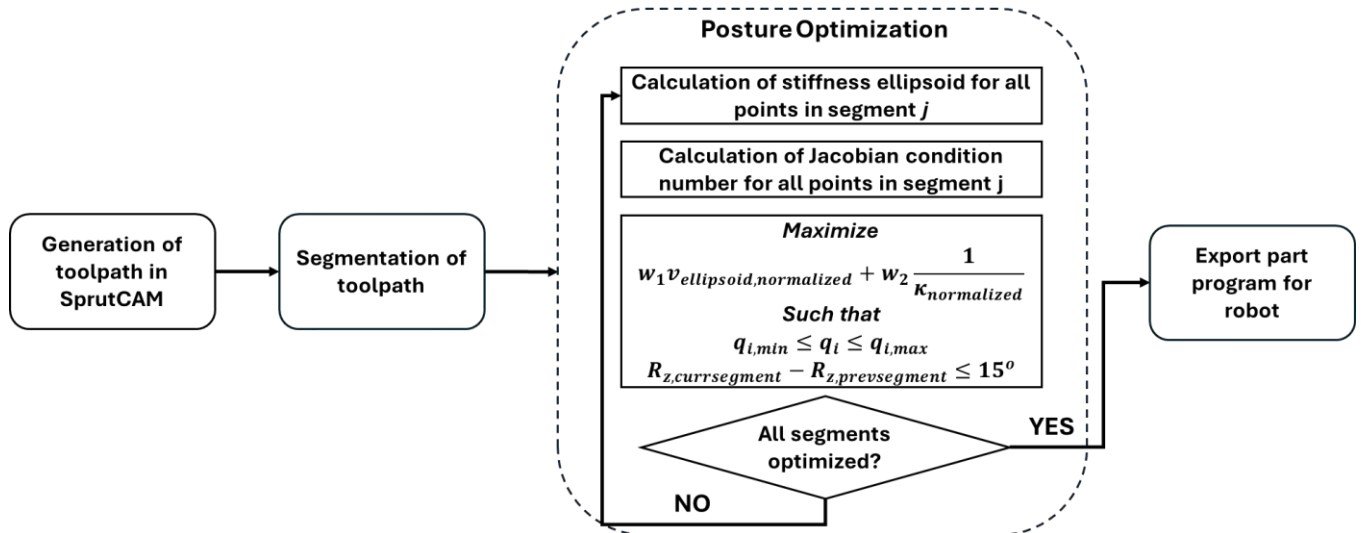


Figure 2.27 Flowchart of the posture optimization algorithm

*Algorithm 2.3 Pseudocode of the posture optimization algorithm***Input:** Toolpath**Output:** Part program of robot

```

1:  load toolpath from file
2:  initialize robot kinematics from URDF file
3:  radii, normals  $\leftarrow$  ComputeCurvatureAndNormals(toolpath)
4:  segments  $\leftarrow$  None
5:  current_segment  $\leftarrow$  toolpath[0]
6:  for  $i \in \{1 \dots N_{\text{toolpathpoints}}\}$ 
7:      if  $\text{radii}[i] - \text{radii}[i-1] > \text{threshold}$  or  $\text{normal}[i] - \text{normals}[i-1] > \text{threshold}$ 
8:          append current_segment to segments
9:          current_segment  $\leftarrow$  None
10:     else
11:         append toolpath[i] to current_segment
12:     end
13: end
14: for segment  $\in$  segments
15:     stiffness_values  $\leftarrow$  None
16:     condition_values  $\leftarrow$  None
17:     for point  $\in$  segment
18:         for  $r_z \in \{-90 \dots 90\}$ 
19:             pose  $\leftarrow$  CreateTCPPose(point,  $r_z$ )
20:             stiffness  $\leftarrow$  CalculateStiffnessEllipsoid(pose)
21:             condition  $\leftarrow$  CalculateConditionNumber(pose)
22:             append stiffness to stiffness_values
23:             append condition to condition_values
24:         end
25:         best_score  $\leftarrow -\infty$ 
26:         best_rz  $\leftarrow$  0
27:         for  $j \in \{0 \dots N_{R_z}\}$ 
28:             normalized_stiffness  $\leftarrow$  stiffness_values[j]/argmax(stiffness_values)
29:             normalized_condition  $\leftarrow$  condition_values[j]/argmax(condition_values)
30:             score  $\leftarrow$   $w_1 * \text{normalized\_stiffness} + w_2 * (1 / \text{normalized\_condition})$ 
31:             if score > best_score and  $\text{rz}[j] - \text{rz\_previous\_segment} < 15$ 
32:                 best_score  $\leftarrow$  score
33:                 best_rz  $\leftarrow$  rz[j]
34:             end
35:         end
36:         update toolpath for segment
37:     end
38: export toolpath in .JBI file
39: end

```

Figure 2.28 showcases the positioning of the proposed methodology within the traditional process planning workflow. In a traditional process planning workflow, the CAD design of the part is delivered to the process planner and it is imported in the CAM software. The process parameters are selected and the toolpath is generated. Finally, the post-processor of each specific machine tool or robot is used to generate the part program. The proposed methodology integrates seamlessly the optimization steps into the traditional workflow. In the proposed workflow, the CAD of the part is delivered to the process planner and it is imported in the workpiece placement optimization tool. The machining features are indicated by the process planner, in the same way as they would be indicated in the CAM software, and the optimal placement and orientation of the workpiece is calculated. Then, the process planner imports the CAD in the CAM software, using also the information from workpiece placement optimization to define the setup of the part in the machining cell. The process parameters are selected and the toolpath is generated. Finally, the posture optimization tool calculates the optimal posture along the whole toolpath and modifies the joint angles of the robot at each toolpath point accordingly. It also acts as a post-processor for robot to generate the part program. Following the proposed workflow, the process planner only needs to add an extra step (workpiece placement optimization), which does not need any expertise from their side to be executed. By ensuring that each algorithm is implemented through software tools that are, on the one hand, easy to use and do not require expert knowledge and, on the other hand, well-interfaced with the CAD/CAM systems that are used in the traditional workflow, the industrial viability of the methodology can be ensured.

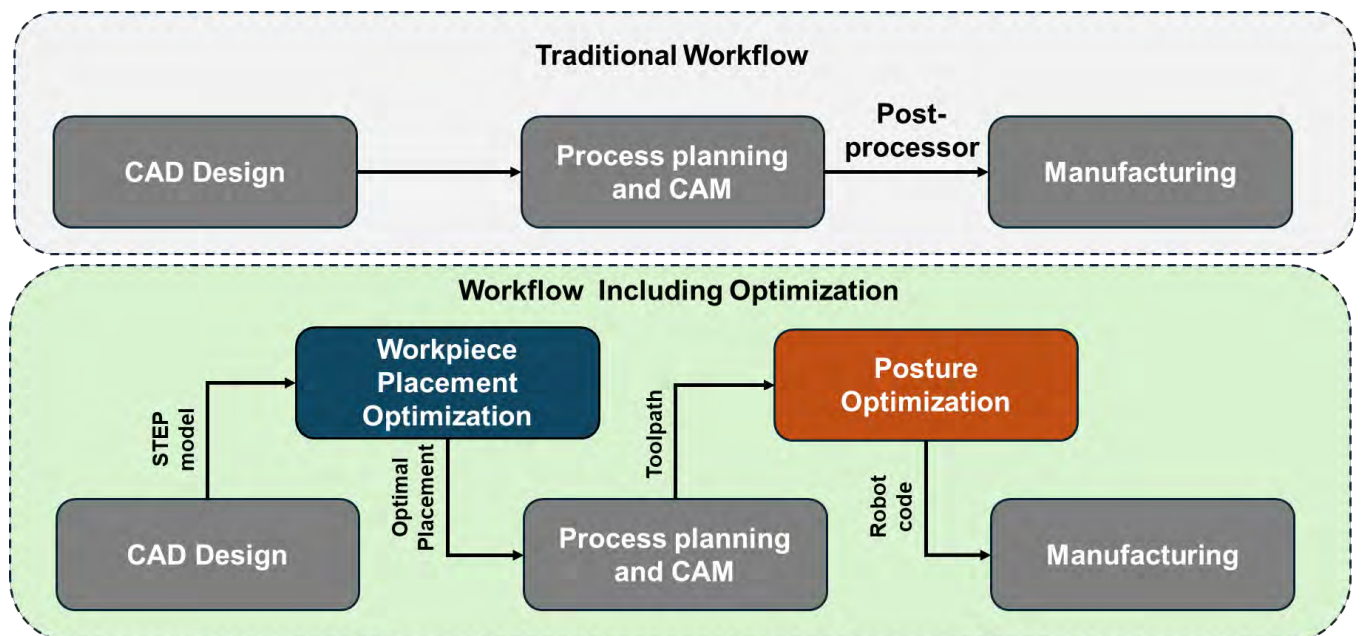


Figure 2.28 Positioning of the proposed methodology within the traditional process planning workflow

2.8. Case Study & Validation

In order to demonstrate the effectiveness of the optimization approach, a case study part was designed (Figure 2.29), having a set of features that enable to test different quality metrics of a machining process. The design of the part comprises of three main machining features: (i) a circle at the center, which is going to be used to test dimensional accuracy; (ii) a slot, where dimensional accuracy is going to be measured and (iii) a spline-based profile, which will be contoured, and profile accuracy will be tested. Finally, the topmost surface of the part will be face milled.

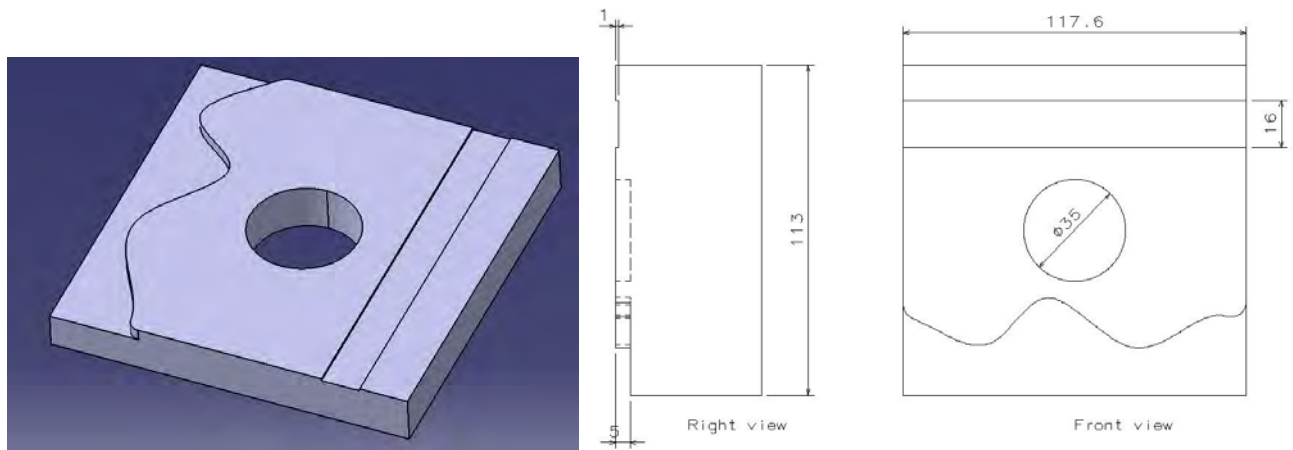


Figure 2.29 3D Model and blueprint of the case study part

The first step is to apply the workpiece placement optimization algorithm. The STEP file of the case study part is imported into the 3D viewer, the machining features are selected and their bounding boxes are calculated (Figure 2.30). Then, the workpiece placement optimization takes place, by calculating first the global optimal placement and then the optimal orientations for each specific feature. The optimal placement is calculated as a translation of the part in the local coordinate system of the table. This coordinate system is parallel with the robot coordinate system and lies on the topmost surface of the table. The results are presented in Table 2.6.

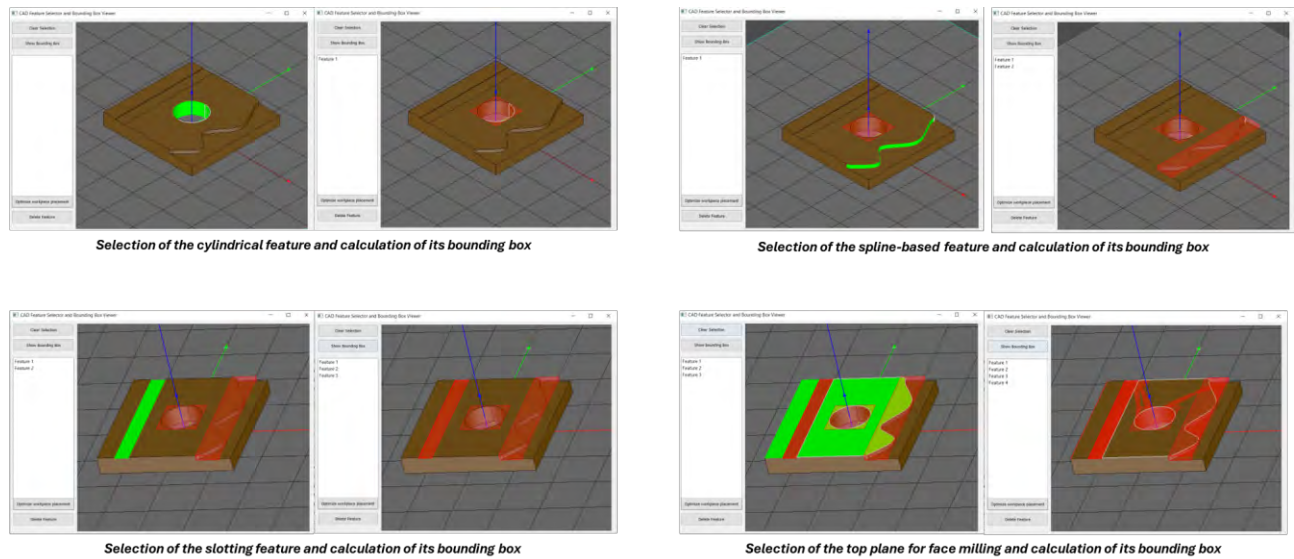


Figure 2.30 Definition of the machining features within the 3D viewer

Table 2.6 Results of the workpiece placement optimization

Feature	Optimal Placement Offset (X, Y, Z) [mm]	Optimal table rotation around X-axis [deg]	Optimal table rotation around Z-axis [deg]
Cylindrical Feature	(-100, 100, 0)	0	0
Spline-based Feature	(-100, 100, 0)	0	270
Slot	(-100, 100, 0)	0	315
Top Plane	(-100, 100, 0)	0	270

Next, the case study part is imported into the CAM software (SprutCAM) to generate the machining toolpaths. The configurations for each feature are input in the CAM, according to the suggestions of the workpiece placement optimization algorithm. Then, the toolpath is exported from CAM and imported into the pose optimization software. First, the segmentation of the toolpaths takes place, as depicted in Figure 2.31. Based on the pose optimization results, a constant value of $R_z = -90^\circ$ for the face milling, slotting and cylindrical features. For the spline-based feature, a variation of R_z within the toolpath is proposed, as shown in Figure 2.32. Figure 2.33 showcases the configurations of the robot, for machining of the different features. For this specific part, the workpiece placement optimization required approximately two minutes of computational time, while the posture optimization algorithm required approximately one minute to be executed, in a typical personal laptop. As a comparison, the part is also machined in a non-optimized position, with constant table orientations (0° for both table rotations) and a constant value of $R_z = 0^\circ$ (Figure 2.34). In both cases,

the vibrations of the robot are being measured with the system described in the Chapter 3, so that they can also be used as an evaluation metric, apart from the geometrical measurements.

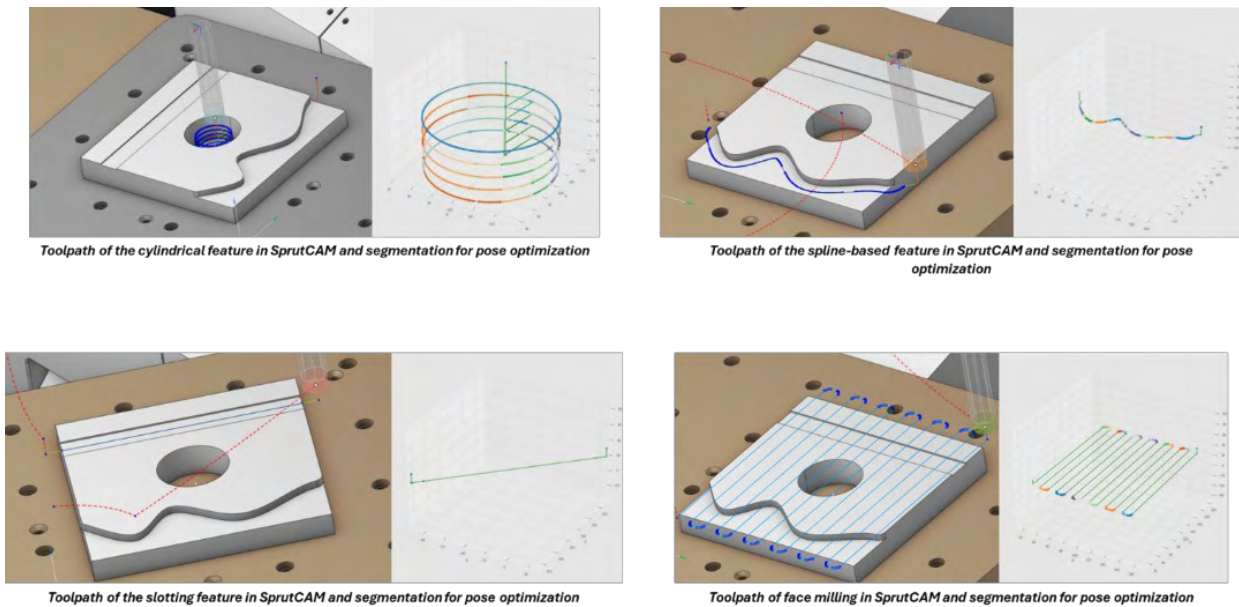


Figure 2.31 The toolpaths generated in SprutCAM and their segmentation

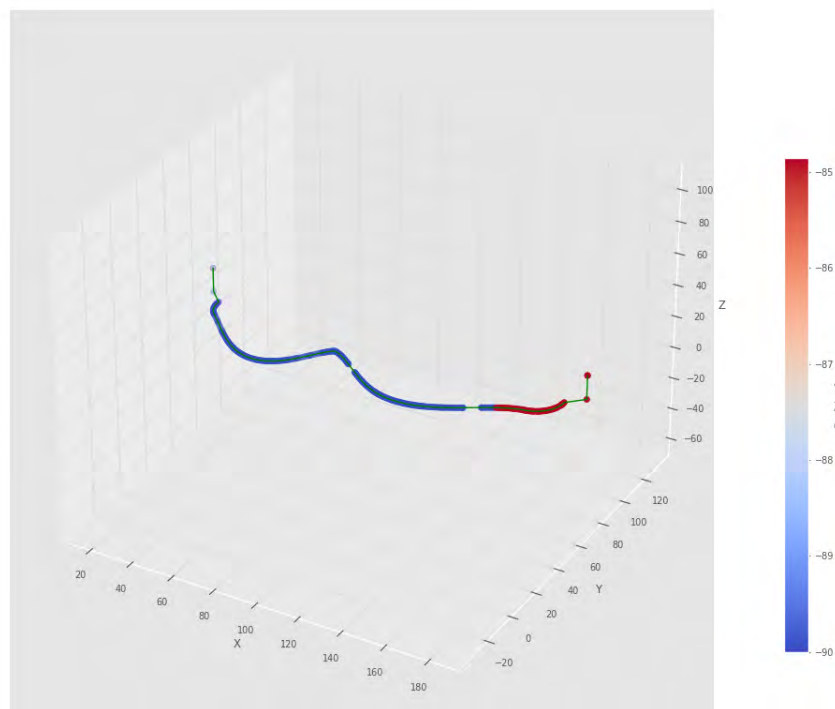
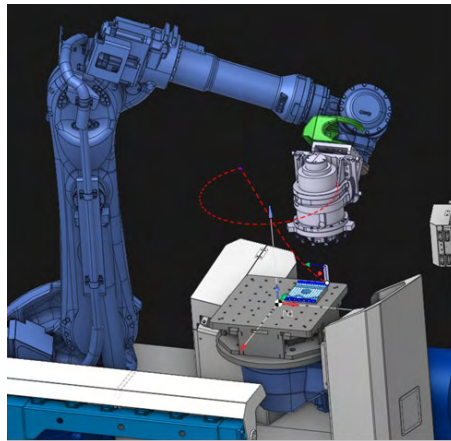
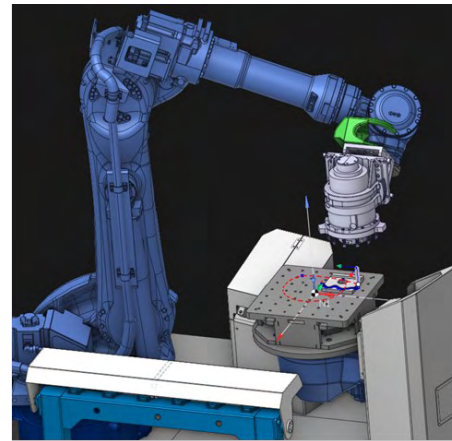


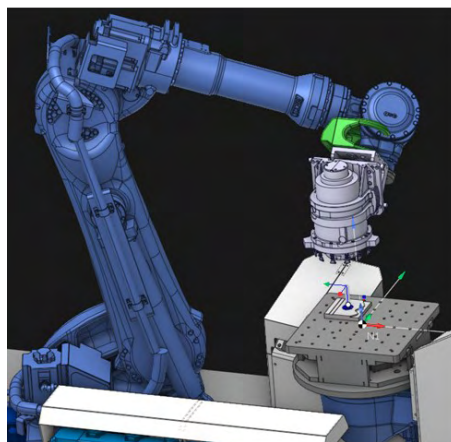
Figure 2.32 R_z values for finishing of the spline-based features



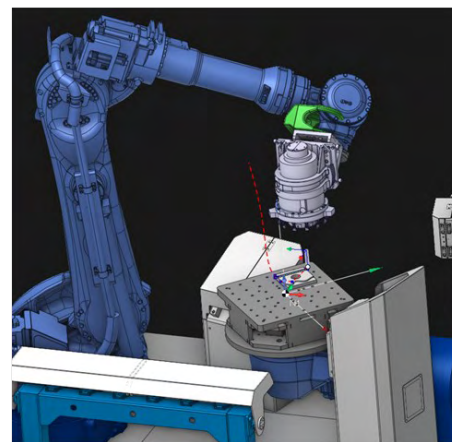
Configuration of the robot during face milling



Configuration of the robot for the spline-based feature



Configuration of the robot for the cylindrical feature



Configuration of the robot during slotting

Figure 2.33 The configurations of the robot for machining the different features

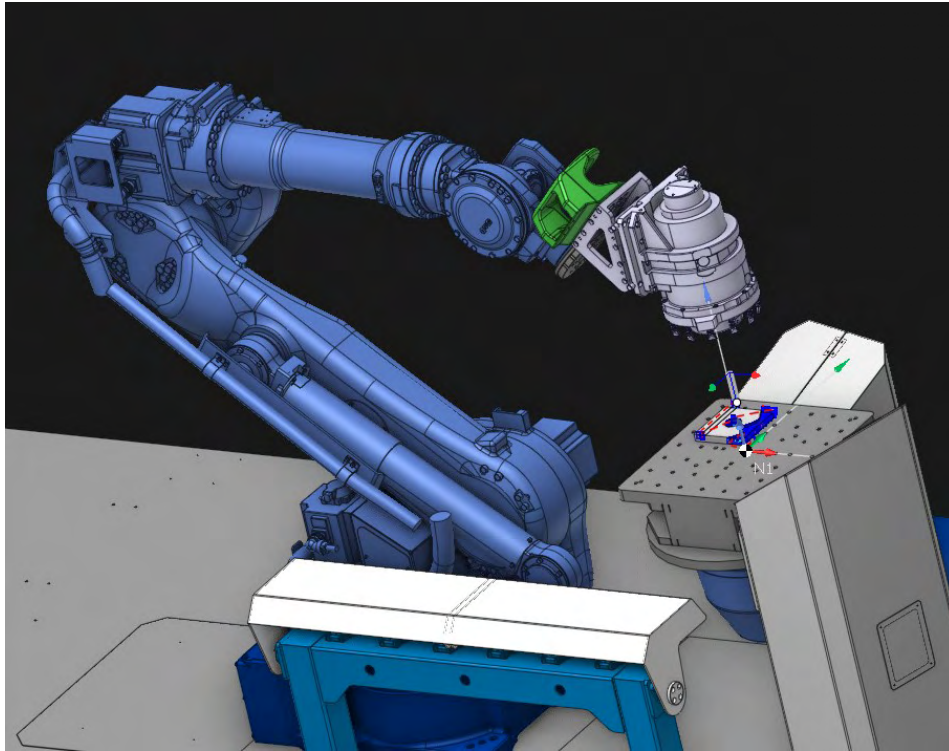


Figure 2.34 Configuration of the robot for the unoptimized case

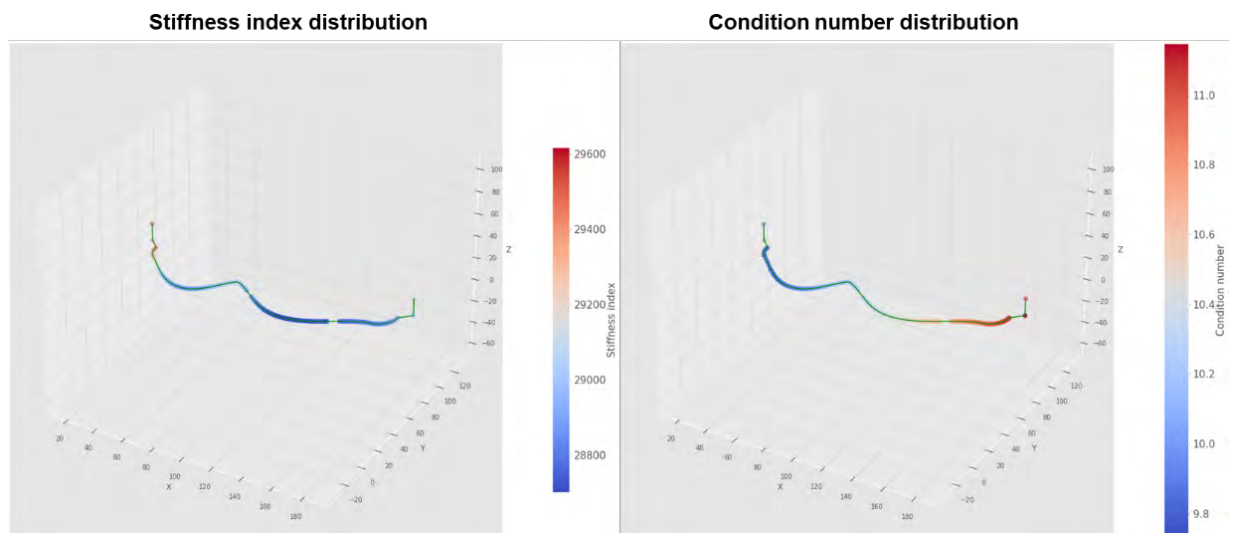


Figure 2.35 Stiffness index and condition number distribution along the toolpath for the unoptimized case

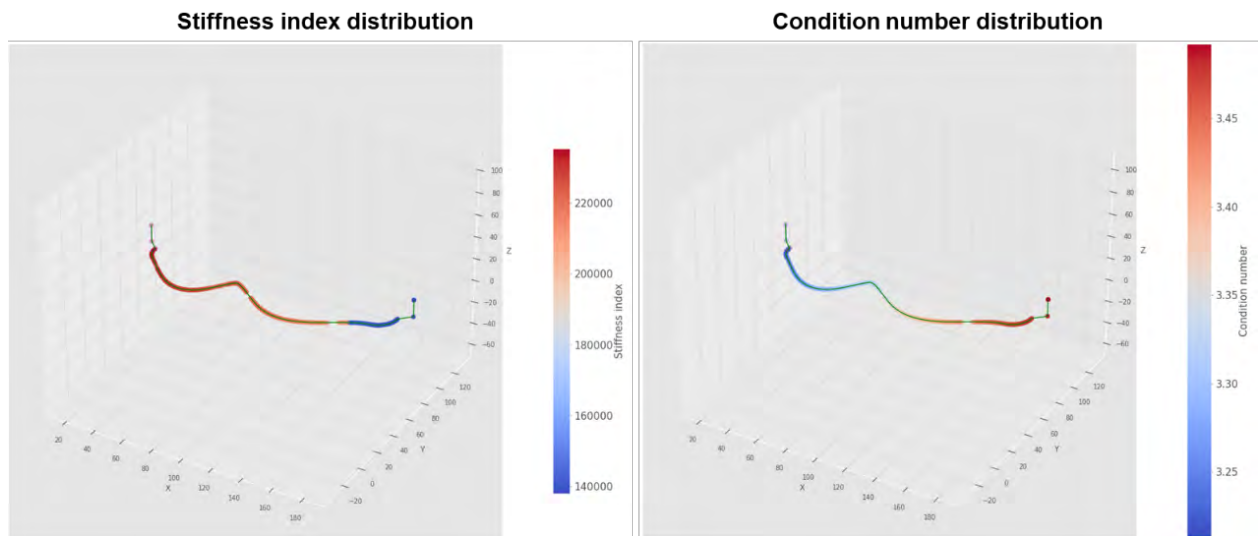


Figure 2.36 Stiffness index and condition number distribution along the toolpath for the optimized case

Figure 2.35 and Figure 2.36 depict the distribution of the condition number of the Jacobian and the stiffness index along the toolpath for the unoptimized and optimized case respectively. These two figures correspond to the toolpath used for machining the spline-based feature and can be used as an example to understand how the posture optimization can affect the performance of the robot. Considering the stiffness index, this is improved by an order of magnitude compared to the unoptimized case, highlighting the significant increase in stiffness that can be achieved through posture optimization. At the same time, the condition number is reduced by more than 50% compared to the unoptimized case. This means that the kinematic performance of the robot is not only preserved but is significantly improved compared to the unoptimized case.

The coupons have been machined for the unoptimized and optimized case, according to the configurations presented above. The cutting tool that was used was a Sandvik R390-016A16-11L indexable milling cutter (16mm diameter) and the cutting inserts were Sandvik R390-11 T3 04E-NL H13A. The process parameters were selected according to the recommended process window of the manufacturer for aluminium machining. The cutting speed was 530m/min, the feed per tooth was 0.05mm, the radial immersion was 6.25% of the cutter diameter (1mm) for the cylindrical feature and the spline-based feature, 45% of the cutter diameter (7.2mm) for face milling and full immersion for the slotting process. The axial depth of cut was 31.25% of the cutter diameter (5mm) for the cylindrical feature and the spline-based feature, 2.5% of the cutter diameter (0.4mm) for face milling and 6.25% of the cutter diameter (1mm) for the slotting process. Figure 2.37 showcases the robot during the machining process for the optimized case. Figure 2.38 presents the machined coupons.



Figure 2.37 Machining of the coupon for the optimized case

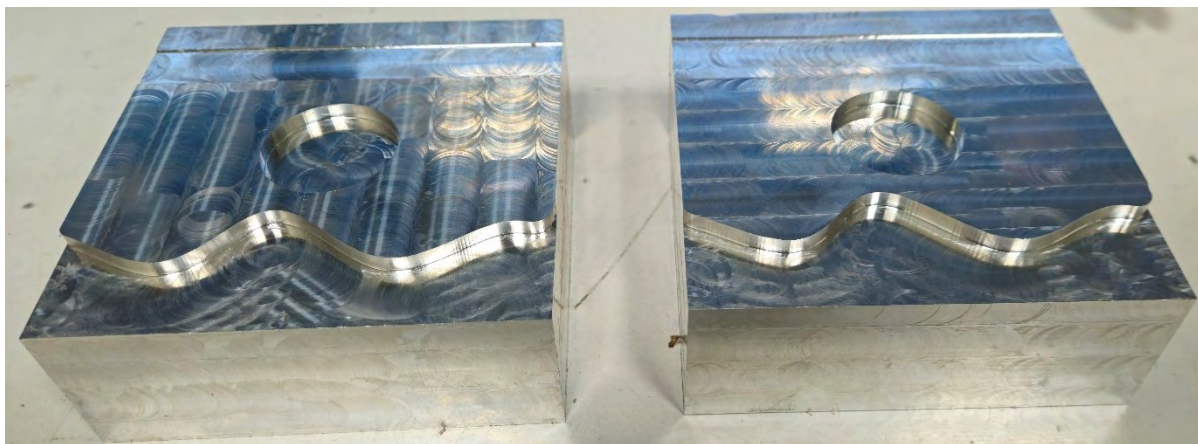


Figure 2.38 The machined coupons; unoptimized case on the left and optimized case on the right side

The dimensions of the cylinder (diameter and depth), slot (width and depth) and the depth height of the spline-based feature were measured with a micrometer. Three measurements were sampled for each feature. At all cases, the reading was consistent among the measurement samples. To evaluate the profile accuracy, the points of the spline-based feature were traced using images from an INSIZE ISM DL-300 microscope. A spline was fit through these points, using the NURBS-Python package [2.60]. The spline was compared with the nominal spline that was generated in the CAD model. The mean and maximum chord error are calculated and used to evaluate the profile accuracy of the spline-based feature. Table 2.7 presents the results of the measurements taken on the two coupons, as well as the nominal dimensions, based on the CAD file. It can be observed that in the optimized case, the robot performs consistently better in all cases, except for the slot milling. In this case, both the optimized and unoptimized configurations yield the nominal dimensions. This means that the machining load during slot was not enough to create large deformations and reduce the process accuracy.

Table 2.7 Results of the geometrical measurements

Feature	Unoptimized	Optimized	Nominal
Circle Diameter [mm]	34.90	35.00	35.00
Circle Depth [mm]	5.10	5.05	5.00
Spline Depth [mm]	5.10	5.00	5.00
Slot Width [mm]	16.00	16.00	16.00
Slot Depth [mm]	1.00	1.00	1.00
Chord error mean [mm]	0.022	0.021	-
Chord error max [mm]	0.161	0.158	-

The vibrations of the machining robot during the processing of different features have been recorded, utilizing the vibration monitoring system that is described in the Chapter 3. A simplified metric is calculated to provide an overview of the effect of pose optimization on the robot vibrations. For that purpose, the mean vibration amplitude of each axis is presented, as well as the mean total vibration energy $\overline{E_{total}}$ from all three axes, which can be calculated as follows:

$$\overline{E_{total}} = \frac{1}{n} \sum_{i=1}^n a_{x,i}^2 + a_{y,i}^2 + a_{z,i}^2 \quad (2.25)$$

where n is the number of samples in a machining signal and a_x, a_y, a_z are the vibrations in the X, Y and Z axes respectively.

The results of the robot vibrations are presented in Table 2.8. By observing these results, a number of conclusions can be drawn. In the case of the cylindrical feature, the mean amplitude in the Z-axis rises to 0.920g for the optimized case, compared to 0.667g the unoptimized. In the face milling case, the vibration differences are negligible for all axes. In the slotting case, there is a marginal vibration reduction in the Z-axis (0.229g for the optimized compared to 0.258g for the unoptimized), together with a significant decrease in X and Y axes. In the spline-based feature a marginal increase is observed in the Z-axis (0.677g for the optimized case compared to 0.609g for the unoptimized), together with a significant decrease in X and Y axes. The reason that in some cases an increase in Z-axis vibration might occur is that the optimization algorithms favour solutions for workpiece placement and posture that lead to the increase of stiffness in the directions of the normal vectors of the machined surfaces and toolpaths respectively. In the specific case study parts, these directions lie on the XY plane. Nevertheless, in all cases (except for the face milling, where the differences are negligible), the mean total vibration energy ($\overline{E_{total}}$) is significantly reduced (31% - 66%, depending on the case). Again, the improvement, thanks to the workpiece placement and pose optimization, is clear. This is also demonstrated in Figure 2.38, where it can be observed that the vibration marks in the optimized case are less prominent than the vibration marks in the unoptimized case.

Table 2.8 Robot vibrations during milling of the different features

Feature	Unoptimized				Optimized			
	$\overline{a_x} [g]$	$\overline{a_y} [g]$	$\overline{a_z} [g]$	$\overline{E_{total}} [g]$	$\overline{a_x} [g]$	$\overline{a_y} [g]$	$\overline{a_z} [g]$	$\overline{E_{total}} [g]$
Cylindrical Feature	1.132	1.077	0.577	0.667	0.802	0.794	0.920	0.458
Spline-Based Feature	1.245	1.097	0.609	0.676	0.642	0.614	0.677	0.318
Face Milling	0.265	0.244	0.201	0.052	0.254	0.244	0.206	0.051
Slotting	0.365	0.339	0.258	0.108	0.189	0.185	0.229	0.036

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3. CHAPTER 3. IN-PROCESS CHATTER DETECTION

3.1. The Phenomenon of Chatter in Milling

During a milling process, the cutting forces that are generated at the tool-chip interface, due to the plastic deformation and breakage of the workpiece material, are a function of the chip thickness and have a periodic nature. This periodicity can be determined by the tooth passing frequency (frequency at which a cutting edge of a multi-tooth cutting tool enters the workpiece) or the spindle rotational frequency, depending on factors such as unbalances, tool holder or cutting tool runout, etc. In any case, the cutting force will be periodic around one of these two frequencies and have strong harmonics up to four or five times the fundamental frequency. Due to this periodic excitation, the machine tool-tool holder-cutting tool-workpiece system exhibits forced vibrations under the fundamental frequency and/or its harmonics. This is a normal aspect of the milling process and is not fully avoidable; however, it is possible to control the amplitude of these vibrations by controlling the cutting forces. These vibrations are responsible for the surface generation in a milling process and are directly tied to the surface roughness of the machined part. Apart from these vibrations, there are also self-excited vibrations that might take place in the milling process. This results in the phenomenon of chatter, which is detrimental for the part quality, cutting tool life and machine tool health (Figure 3.1).

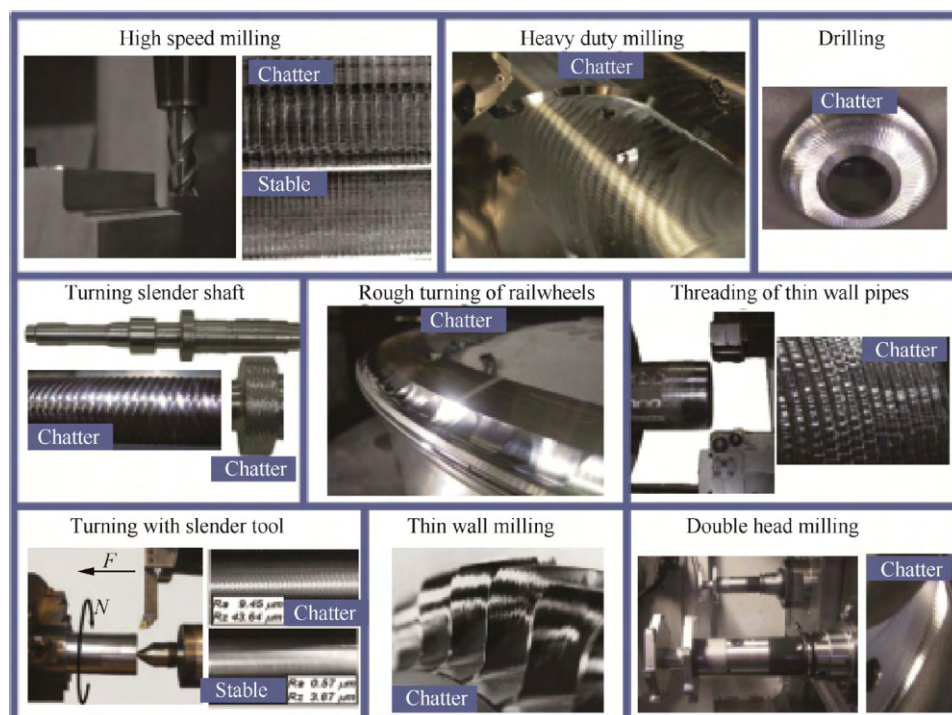


Figure 3.1 Effect of chatter vibrations in machining [3.1]

Chatter vibrations are a result of a self-excitation mechanism during chip generation in milling. Initially, one of the structural modes of the machine tool-tool holder-cutting tool-workpiece system is excited by the cutting forces. The vibration of the cutting tool in the plane of cut, which is defined by the feed direction and radial direction of the cutting tool, is a two-degree-of-freedom vibration, one along the feed direction and one along the radial direction of the cutting tool. The cutter can be considered suspended on two spring-damper systems, one per vibration direction (Figure 3.2). The stiffness and damping coefficients can be determined by the calculation of the global stiffness, as described in Chapter 2. The tool starts vibrating around the frequency of the structural mode, so the generated surface presents a waviness with a frequency equal to the frequency of the structural mode. When the next tooth enters the cut, it meets a variable chip load that oscillates at a chatter frequency that is close, but not equal to, a dominant structural mode of the system. This is a mechanism for the generation of self-excited, regenerative chatter vibrations. The two types of chatter are regenerative and mode-coupling chatter. Mode-coupling chatter takes place when the vibrations exist in the two axes in the plane of cut [3.2].

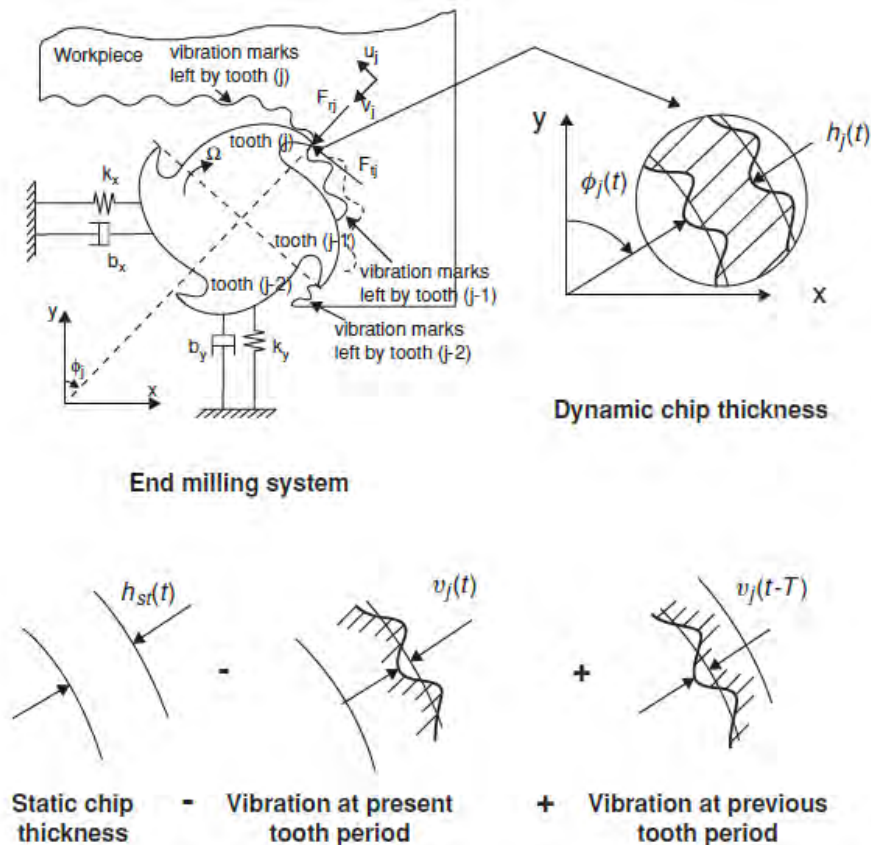


Figure 3.2 Chatter vibrations due to the regenerative phenomenon [3.2]

In the context of robot machining, there is a peculiarity observed, which is a result of the lower structural stiffness of the robot, compared to CNC machining centers. Specifically, in robot machining low-frequency chatter (LFC) and high-frequency chatter (HFC) can be observed. The former is dominated by the structural modes of the robotic arm, while the latter is dominated by the structural

modes of the spindle and/or the cutting tool. The distinction between LFC and HFC is relevant only for robot machining, because in the cases of CNC machining centers, there is no significant dispersion between the structural modes of the machine tool and the structural modes of the other components, as is the case with robot machining. In practice, LFC is only observed in robot machining and is usually tied to a mode coupling phenomenon, while HFC is what has been traditionally observed in machining processes, before robot machining. LFC is more likely to be excited in heavy-duty milling and results in significantly larger vibrations, compared to HFC, so it cannot be overlooked [3.3].

In general, physics-based models have been proposed for chatter, addressing all types of milling processes (3-axis, 5-axis, thin-walled workpieces, robotic milling). In order to model chatter, one must solve the delay differential equation (DDE) that governs the phenomenon in the time-frequency domain. In most practical cases, it is only necessary to determine the stability boundary of the process. For a specific machine, tool holder, cutting tool and workpiece material and a given set of process parameters (radial depth of cut and feed per tooth), the stability limit can be determined, in terms of axial depth of cut, for a specific spindle speed. By scanning the available speeds that the spindle can achieve, one can generate the stability lobe diagrams (SLDs), which determine the stability boundary of the process and can be useful for process planning. Of course, by making the radial depth of cut and feed per tooth variable, the stability boundary can be expressed in three and four dimensions, respectively [3.4]. Figure 3.3 depicts an SLD for a typical milling process.

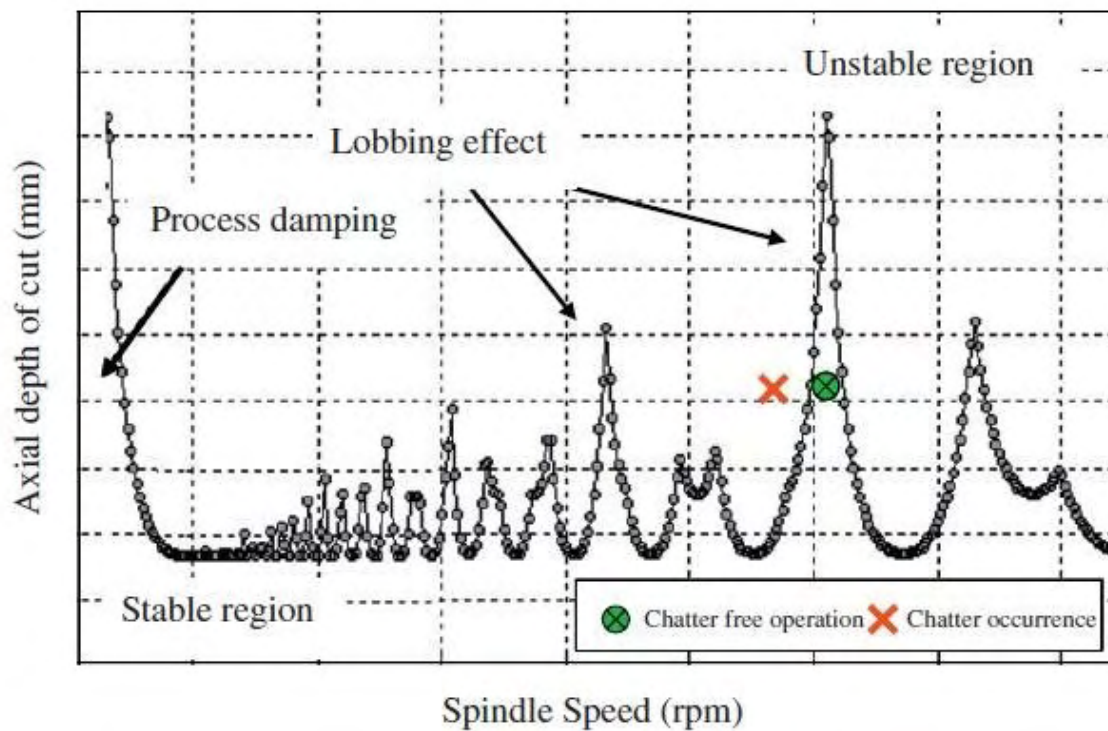


Figure 3.3 A stability lobe diagram of a typical milling process [3.5]

Although chatter modelling can be very useful for process planning, the modelling process can become quite complex. The available physics-based models for chatter require the knowledge of the Frequency Response Function (FRF) of the machine. To determine that, testing the machine tool with an impact hammer is required (Figure 3.4), which requires costly equipment and high expertise. In the context of robotics, the process becomes much more complex, since the position and posture-dependent dynamic behaviour, which has been explained in Chapter 2, leads to a position and posture dependent FRF. An approach is to perform multiple impact tests in different positions and postures and try to interpolate the rest of the working volume. However, the accuracy of this process is significantly limited [3.6].



Figure 3.4 Testing of a machine tool with an impact hammer [3.7]

Considering the aforementioned, it is evident that trying to predict the absolute stability limit of the process is not practical in most cases, especially in robot milling. So, the solution to that problem is to implement chatter monitoring systems, which can detect the presence of chatter in-process and allow the operator to apply corrective actions (usually by changing the spindle speed to move horizontally in the SLD and fall under a stability lobe). As such, the scope of the second pillar of this research is to develop a monitoring system for detecting chatter in-process, while considering all the requirements that have been defined in Chapter 1, to promote industrial adoption. As such, the system is based on low-cost, industrial-grade equipment (sensors and electronics), is easy to retrofit in existing machining robots and machine tools and uses a generalizable, AI-based approach to achieve chatter detection.

3.2. State of The Art in Chatter Monitoring in Milling

Chatter is one of the most important challenges for machining processes and has been researched for several decades. As a result, the available literature on the topic of chatter monitoring is immense. In this section, a collection of relevant, recent approaches is presented, in order to provide the reader with an overview of the current State of The Art. The main differences among the various approaches can be pinpointed to the type of sensors used, the algorithms used for signal analysis (in time, frequency or time-frequency domains) and the existence or not of an automated approach for chatter detection. Especially in the latter, the use of AI is prominent, so differences can also be observed in the AI models selected by the authors.

Liu et al [3.8] have used a piezoelectric dynamometer to capture the cutting force during milling. Then, using Variational Mode Decomposition (VMD), they decomposed the signals and tracked the evolution of the energy entropy on the Intrinsic Mode Functions (IMFs) that were close to chatter

frequencies. They demonstrated that the energy transfer from harmonic vibration IMFs to chatter IMFs could be utilized for chatter detection. Yang et al. [3.9] also adopted VMD in their approach, which was based on cutting force signals, to identify chatter by tracking the evolution of approximate and sample entropy on the IMFs. They demonstrated that this method has the potential to identify chatter at its onset. Zhang et al. [3.10] utilized VMD together with Wavelet Packet Decomposition (WPD) and calculated the energy entropy of the signals as a chatter indicator. In their discussion, they mentioned that although the method was promising, its accuracy was highly dependent on the correct configuration of VMD and WPD by the user. This highlights the limitations of complex methods that require significant user expertise, when it comes to adoption in real, industrial scenarios. Li et al. [3.11] used Angular Synchronous Averaging (ASA), in order to eliminate the harmonic component from the cutting force signal. In the residual signal, which they considered as directly related to chatter, they calculated the Multiscale Permutation Entropy (MPE) and Multiscale Power Spectral Entropy (MPSE), which were used as inputs for a Gradient Tree Boosting classifier to detect chatter.

The other popular method for chatter detection is through vibration monitoring. Perez-Canales et al. [3.12] calculated a randomness index for vibration signals in milling and used it as an indicator for chatter occurrence, based on a user-defined threshold. Signal decomposition is also popular in vibration monitoring. Chen et al. [3.13] applied Ensemble Empirical Mode Decomposition (EEMD) on vibration signals and calculated a wide set of statistical features from the decomposed IMFs. These were input to a Support Vector Machine (SVM) classifier to detect chatter. Ji et al. [3.14] utilized EEMD to remove the harmonic part of the signal and reconstruct the residual signal. Then, by segmenting the residual signal with Fractal Dimensions and calculating the Power Spectral Entropy (PSE), they were able to find correlation with the presence of chatter. Fu et al. [3.15] used EEMD to decompose the vibration signal and calculated the principal energy of each IMF to characterize its correlation with chatter. Based on that, they were able to classify the process between stable and unstable. Another interesting approach was presented by Chen et al. [3.16]. In their work, they calculated the spectrograms of the vibration signals and treated them as images. By applying image processing algorithms on the spectrogram images, they calculated image-related features that were used as inputs for an SVM classifier to detect chatter.

Sensor fusion has also been proposed for chatter detection. For example, Kuljanic et al. [3.17] have proposed a combined cutting force and vibration monitoring system. The signals were decomposed with WPD and statistical features (mean, standard deviation, skewness) were extracted from the decomposed signals. Based on these input features, they trained a Neural Network to detect chatter.

Other, non-conventional sensing approaches can also be identified in literature. Alsan and Altintas [3.18] utilized the spindle motor current data. They applied a comb filter to filter out the signal components, related to the tooth passing frequency. Then, they used the Direct Fourier Transform (DFT) on the residual signal and applied a user-defined threshold on its magnitude, after which the

process becomes unstable. Cao et al. [3.19] used a microphone to record the sound generated during the milling process. Then, they applied a synchrosqueezing transform to the signal, in order to remove the components related to the tooth passing frequency and its harmonics. Next, they also applied Singular Value Decomposition on the time-frequency domain representation of the residual signals and used a user-defined threshold to determine the presence of chatter.

Specifically, in the context of robot machining, Chen et al. [3.20] proposed an approach based on the VMD, with a real-time optimization of its hyperparameters, using cross entropy of the image as a chatter indicator. The key focus of their approach was to compensate for the posture dependent dynamics of the robotic arm. An adaptive version of VMD was also used by Chen et al. [3.21] coupled with entropy-related features to identify chatter frequencies in the vibration signal. Entropy features on the time domain representation of the signal have also been utilized by Yang et al. [3.22] who utilized EEMD to decompose the vibration signal during robot machining and train a Support Vector Machine model to detect chatter during robot machining. Other sensing approaches include the integration of acoustic emission sensors, as in the work of Li et al. [3.23] who installed the acoustic emission directly on the workpiece during robot machining of CFRP composites. They correlated the amplitude of the acoustic emission signal with the existence of chatter in the process. In another work of the same authors [3.24], they examined again the application of acoustic emission sensors for chatter detection in high-speed robotic milling, using the root mean square value and Fourier transform of the signal as indicators of the presence of chatter. A common characteristic of the works on robot machining is that they focus on HFC. However, LFC is a phenomenon that is equally prominent in robot machining, while it can be the main chatter-related phenomenon when heavy duty milling with large, rigid tools is performed.

3.3. Description of the Measurement Setup

The in-process chatter detection system was developed using the same robot machining cell that has been described in Chapter 2. However, the system is not limited to robot machining operations and can also be used in CNC machining centers, something that will be discussed towards the end of this chapter. The sensing setup is comprised of a Micromega IAC-CM-U tri-axial, MEMS accelerometer, which is integrated on the spindle head (Figure 3.5).

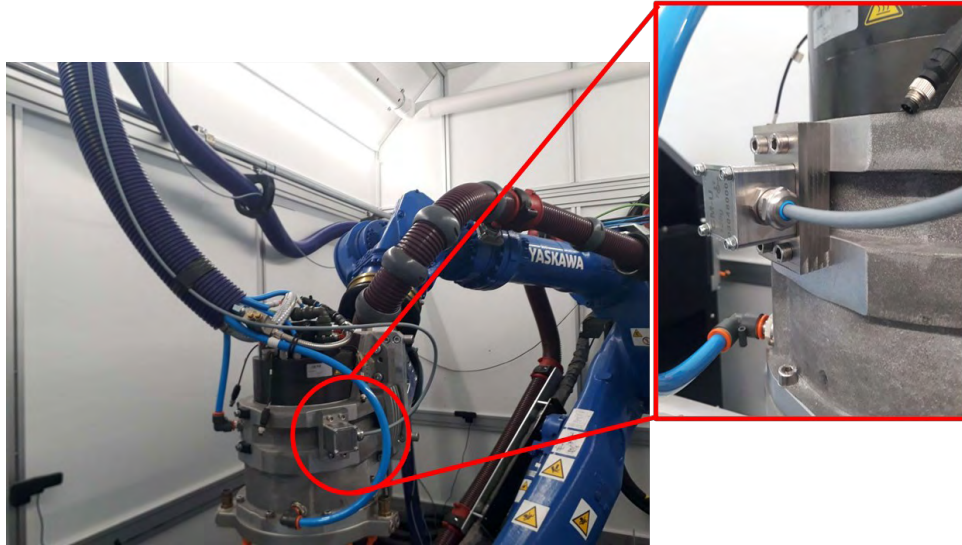


Figure 3.5 Integration of the accelerometer on the spindle head

The signals are captured from the accelerometer using a Labjack T8-Pro Data Acquisition Device (DAQ) and streamed in real-time to a computer stationed next to the robot cell, using the Python APIs of the DAQ, communicating with the ModBus protocol. The sensor receives a voltage input directly from the low-voltage circuit of the electrical cabinet of the robot and is grounded together with the DAQ in the grounding stud of the cabinet. As such, errors due to ground offsets between the sensor and DAQ are minimized, while making the whole system more robust and industrialized. Additionally, using a custom Python script the computer communicates with the robot controller, using the High-Speed Ethernet Server of Yaskawa. Through this communication channel, the robot position and orientation are retrieved, along with the spindle speed allowing for mapping of the vibration data on the robot coordinate system, as well as angular sampling of the data. The software architecture is depicted in Figure 3.6.

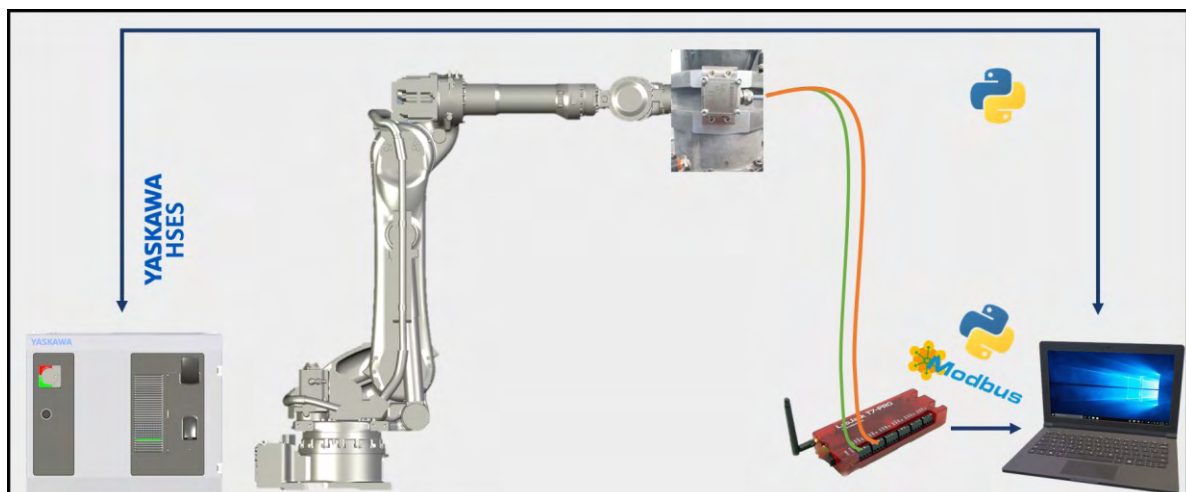


Figure 3.6 Monitoring system architecture

The detailed specifications of the sensor and DAQ are presented in Table 3.1 and Table 3.2 respectively.

Table 3.1 Specifications of the Micromega vibration sensor

Specification	Value
Measurement range [g]	± 25
Output range [V]	0 – 5
Bandwidth [Hz]	0 – 10000 (-3dB)
Non-linearity	0.5% of Full Scale (F. S.)
Transverse sensitivity	2% of nominal sensitivity
Temperature sensitivity drift [ppm/°C]	± 500
Temperature offset drift [g/°C]	± 0.05
X-axis Calibration data	
Sensitivity [mV/g]	81.200
Gain [g/V]	12.3153
Offset [V]	2.522
Y-axis Calibration data	
Sensitivity [mV/g]	80.640
Gain [g/V]	12.4008
Offset [V]	2.450
Z-axis Calibration data	
Sensitivity [mV/g]	79.820
Gain [g/V]	12.5282
Offset [V]	2.548

Table 3.2 Specifications of the Labjack T8 DAQ

Specification	Value
RMS Bits	18.3
Noise-Free Bits	15.6
Effective Resolution RMS [μV]	29.7
Effective Resolution Noise-Free [μV]	193.3
Sampling Rate [Hz]	10000

Before proceeding with the analysis of the vibration signals, it is important to perform an uncertainty analysis on the signals, since the system is self-developed. This validates the quality of the incoming data. The overall signal uncertainty (per accelerometer axis) can be expressed as follows:

$$u_c = \sqrt{u_{quant}^2 + u_{drift}^2 + u_{sensitivity}^2 + u_{nonlinearity}^2} \quad (3.1)$$

where:

- u_{quant} is the quantization error of the DAQ device
- u_{drift} is the error due to offset drift of the sensor
- $u_{sensitivity}$ is the error due to the sensitivity drift of the sensor
- $u_{nonlinearity}$ is the error due to the nonlinearity of the sensitivity across the measurement range

Quantization error arises from the finite resolution of the analog-to-digital converter (ADC) within the DAQ device. The effective resolution (RMS) for the LabJack T8 is 29.7 μV and noise-free uncertainty is 193.3 μV . Given the calibration gain per axis, which is presented in Table 3.1, it is possible to convert this to measurement uncertainty as follows

- $u_{quant,x} = 193.3 \mu V \times \frac{1}{\frac{12.3153g}{V}} = 0.00238g$
- $u_{quant,y} = 193.3 \mu V \times \frac{1}{\frac{12.4008g}{V}} = 0.00240g$
- $u_{quant,z} = 193.3 \mu V \times \frac{1}{\frac{12.5282g}{V}} = 0.00242g$

The robot machining cell (and therefore the monitoring system) operates in a climate-controlled environment, with a temperature ranging between 17–25°C across all seasons. Therefore, the error due to offset drift of the sensor can be calculated as $u_{drift} = 0.0004g$.

The non-linearity uncertainty (0.5% of full scale) can be calculated as $u_{nonlinearity} = \pm 0.125g$.

So, the total uncertainty per axis can be calculated as follows:

- $u_{c,X} = \sqrt{(0.0238g)^2 + (0.0004)^2 + (0.049)^2 + (0.125)^2} = 0.136g$
- $u_{c,Y} = \sqrt{(0.0240)^2 + (0.0004)^2 + (0.049)^2 + (0.125)^2} = 0.136g$
- $u_{c,Z} = \sqrt{(0.0242)^2 + (0.0004)^2 + (0.050)^2 + (0.125)^2} = 0.137g$

Based on this analysis, there are two main conclusions that can be drawn. First of all, the uncertainty level of the measurement setup is relatively small to the expected vibration magnitudes in the milling process, which range several g, as it will also be observed in the next sections. Moreover, the main source of uncertainty is the nonlinearity of the sensitivity of the sensor. This is more prominent towards the extremities of the range of the sensor, so the actual uncertainty during normal operating conditions (where vibrations are not expected to exceed 10-15g) will be significantly smaller.

Next, analysis of the noise floor of the system takes place, using the Allan variance and Allan deviation. Allan variance measures how much the average of a signal changes over time, across different averaging intervals (called taus). It quantifies how stable or noisy a signal is at different timescales. Instead of computing the variance of individual samples (as in classical statistics), Allan variance computes the variance of differences between successive averaged segments of the signal. Considering a time series of evenly sampled data $x(t)$, sampled at a rate f_s , in non-overlapping windows, the Allan variance is calculated as follows:

$$\sigma^2(\tau) = \frac{1}{2(N-1)} \sum_{i=1}^N (\bar{x}_{i+1} - \bar{x}_i)^2 \quad (3.2)$$

where N is the number of averaged segments for that τ . This is the Allan variance for averaging time τ . Its square root is called the Allan deviation (ADEV). Different noise processes dominate at different time scales. The double logarithmic plot of Allan deviation vs the averaging time can reveal them. At short averaging intervals, a slope of -1 in the double logarithmic plot pinpoints to quantization noise from the ADC, whereas a slope of -0.5 pinpoints to white noise generated from the electronics (internal or external to the monitoring system). At mid-range averaging interval, a relatively horizontal double logarithmic plot pinpoints to bias instability, due to the sensor bias drift. At longer averaging intervals, a slope of 0.5 in the double logarithmic plot pinpoints to integrated white noise, whereas a slope of 1 pinpoints to drift in the offset of the sensor. The signal of the accelerometer at an idle state was sampled at 10kHz (sampling rate used in the experiments) for 5 minutes. It is important to notice that in the idle state, the nonlinearity uncertainty does not affect the measurement, since it always remains constant. The Allan deviation is calculated and the results are presented in Figure 3.7.

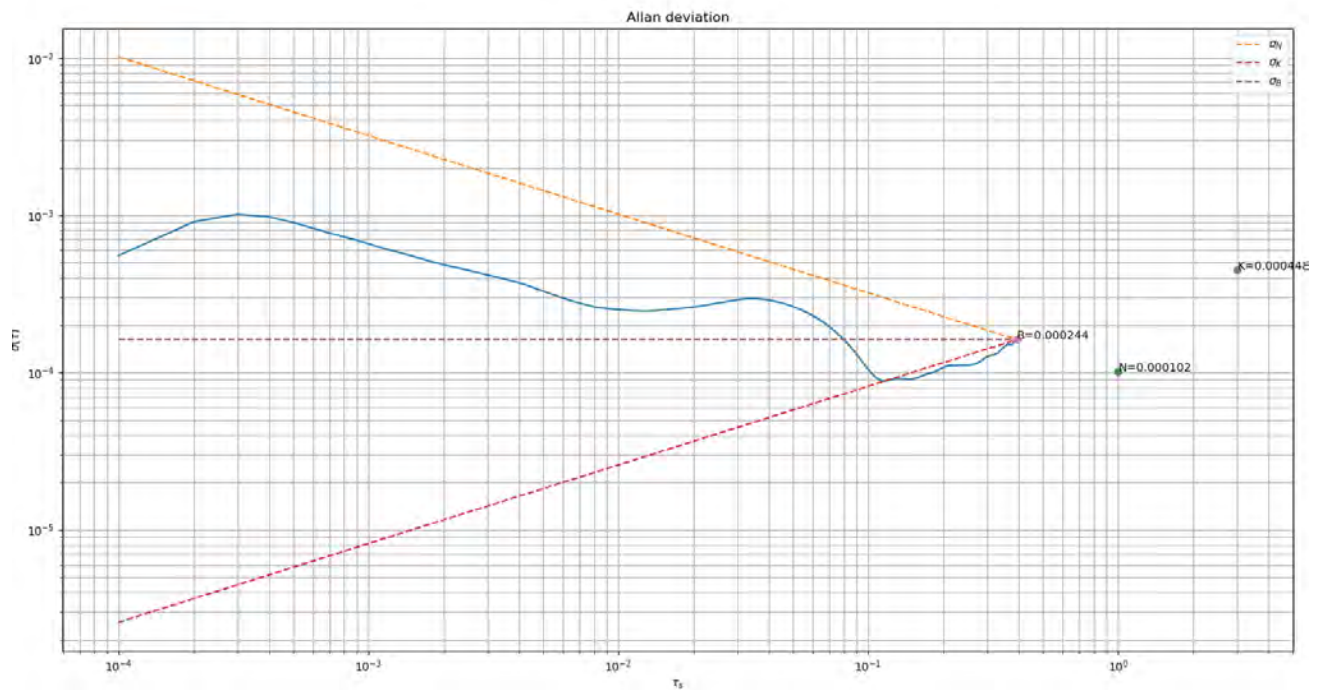


Figure 3.7 ADEV plot for the vibration monitoring system

The graph presented above shows a very low noise floor overall (less or equal than 0.001g). The noise is mainly affected by white noise (potentially caused by the electronics or EMF in the route of the accelerometer cable) in the low averaging intervals and a slight sensor drift in the high averaging intervals.

Based on this analysis, it can be concluded that the monitoring system that has been developed can provide reliable data for further usage towards chatter detection.

3.4. Feature Extraction

The chatter detection approach has been derived under the principle of fulfilling three key requirements: (i) the algorithm should be able to run in real-time during the process, which dictates low computational power for its calculation; (ii) the algorithm should be generalizable enough to be used for different sets of process parameters, cutting tool and workpiece materials and (iii) the algorithm should be agnostic to or compensate for the pose-dependent stability of the robotic arm. Considering the aforementioned and the physical mechanisms that govern the phenomenon of chatter, the main goal is to derive an approach that will capture the transition of the robot vibration from a forced vibration (around the spindle frequency and its harmonics, due to the harmonic cutting force) towards a self-excited vibration (around the chatter frequencies).

The first step of signal processing is filtering the signal. As the robot orientation might be changing constantly (e.g. during 5-axis milling), the 3 axes of the accelerometer might be affected differently

by gravity. A high-pass filter at 40Hz is applied to the vibration signals to eliminate the DC component related to gravity. In any case, at such a low frequency range no significant information are expected to be contained in the signal considering the dynamic response of the whole robot machining cell [3.25].

The next step is the analysis of the signal to identify features that can be linked to the phenomenon of chatter. As explained in the State of The Art section, the vibration can be analyzed in the time, frequency or time-frequency domains. The time-frequency domain analysis is particularly efficient in identifying transient phenomena within a signal, with chatter being a good example of such phenomena; however, resolution is lost compared to analysis in the pure time or frequency domains. The selection of the domain that the signal should be analyzed in, is a compromise based on the signal characteristics and the phenomenon of interest. Figure 3.8 depicts the time-series, Fast Fourier Transform (FFT) and spectrogram of a typical vibration signal from this specific monitoring system. The FFT verifies the low noise floor, since there is no white noise present and all frequency peaks are very prominent and isolated. Additionally, the spectrogram shows that analyzing the signal in the time-frequency domain does not hold significant information. This is a result of the high sampling frequency and small window length (4096 samples). The small window length has been selected, so that the sampling time is short and allows for multiple assessments of the process stability in each second, when the system will be implemented in real-time. Based on these findings, the analysis of the signal and feature extraction will be performed in the time domain and frequency domain individually,

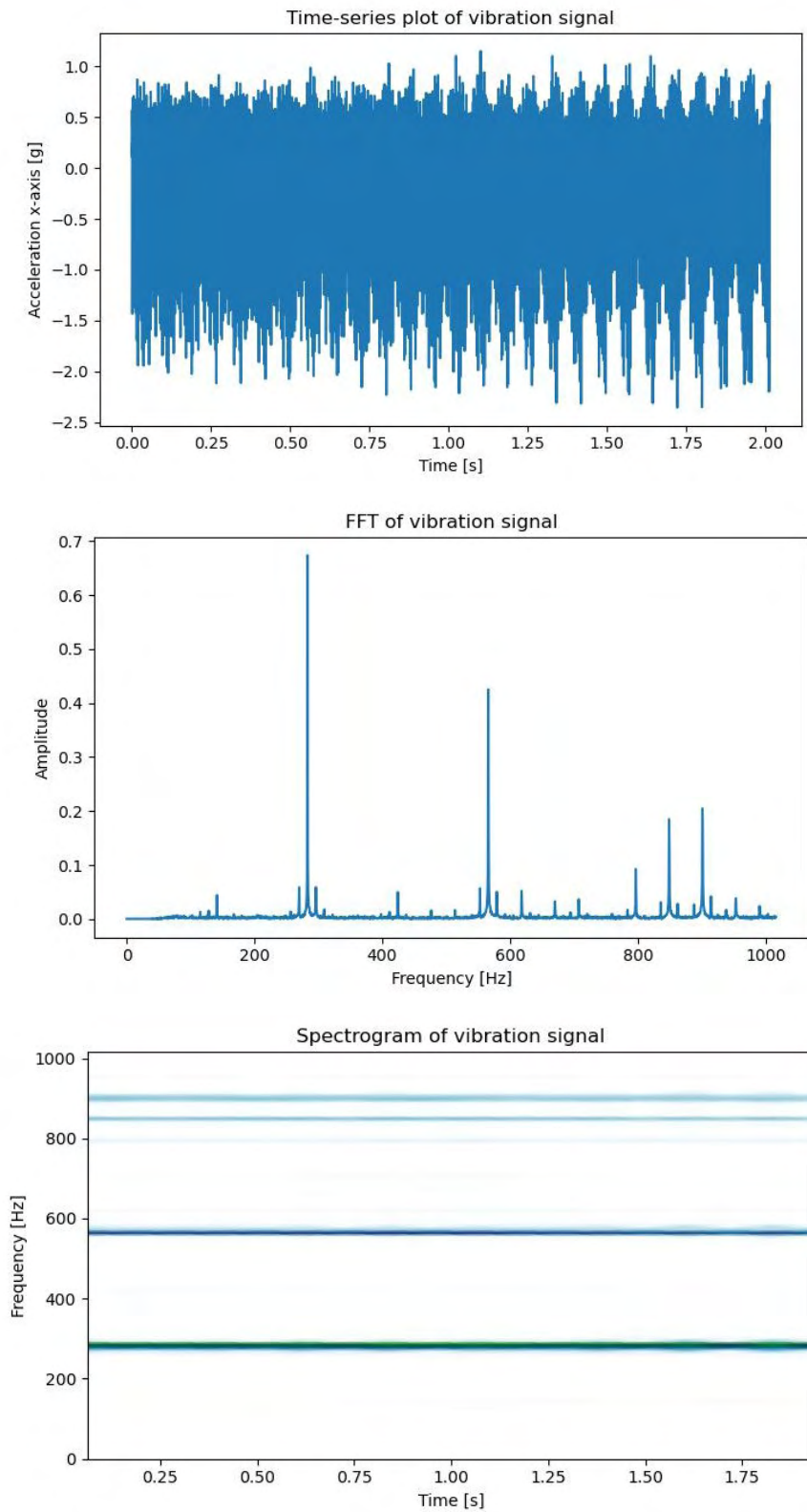


Figure 3.8 Typical vibration signal from the robotic machining cell: time-series (top); FFT (middle); spectrogram (bottom)

The first step towards feature extraction is the investigation of the behavior of the signal in the frequency domain and the identification of the transition of the vibration frequencies from harmonic to chatter. The Fast Fourier Transform (FFT) of the signal is computed and peak picking is performed on the FFT. The frequency peaks that are identified are compared with the spindle rotational frequency and its harmonics. It is important to note here that, although it is commonly mentioned in literature that the tooth passing frequency and its harmonics should be considered, it has been proven that when runout exists in the process, the spindle rotational frequency is the dominant frequency that characterizes the periodicity of the machine tool vibration [3.26]. In real robot machining scenarios, runout will almost always exist, as it is several orders of magnitude smaller than the overall robot accuracy. As such, the dominant frequency of the vibration will be the spindle rotation frequency. The frequency peaks that lie within 5Hz around the spindle rotation frequency or one of its harmonics (to account for numerical errors during the calculation of the FFT) are considered to be harmonic ones. The other frequency peaks are considered to be inharmonic. Then, the first feature, namely the energy ratio, is calculated as follows:

$$\text{Energy Ratio} = \frac{\text{Energy of Inharmonic peaks}}{\text{Sum of energy of total peaks}} \quad (3.3)$$

The energy in Equation 3.3 is considered as the amplitude of the FFT for a given frequency peak. Additionally, the sum of the energy of all peaks is considered in the denominator instead of the energy of the whole FFT, in order to make the algorithm robust to signal noise. A noisy FFT would lead to a large ratio of inharmonic content that would mistakenly be attributed to chatter. Figure 3.9 showcases the way that the transfer of the signal energy from harmonic to inharmonic (chatter) frequencies is reflected in the FFT. On the left side of the figure, the FFT of a stable signal is presented and on the right side of the figure, the FFT of an unstable signal is presented. The blue dashed lines depict the spindle rotation frequency and its harmonics. In the stable case, the vibration signal is gathered around the spindle rotation frequency and its harmonics exclusively, with the tooth passing frequency (signal corresponds to milling with a two-flute cutting tool) being dominant. In the chatter case, some inharmonic frequencies start to appear in the signal. The significance of these frequencies compared to the overall energy of the signal reflects the severity of chatter.

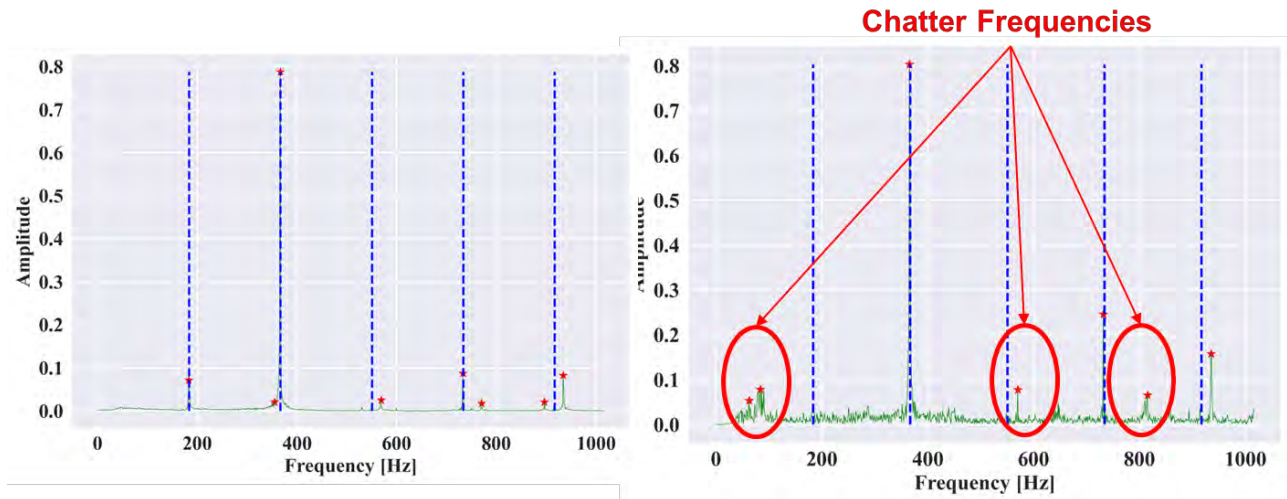


Figure 3.9 Use of FFT peaks as a chatter-related feature; stable signal (left) and unstable signal (right)

Next, the signal is examined in the time domain. The second feature that is examined is the cyclostationarity of the signal in the time domain. The term “cyclostationary” refers to a phenomenon that is not stationary but varies periodically with respect to a variable (time, angle, etc.). This periodicity is exhibited in the statistical moments (mean, variance, etc.) of the phenomenon and the order of cyclostationarity is determined by the order of the statistical moment that exhibits the periodicity [3.27]. A cyclostationary signal is a signal whose statistical properties vary periodically in time. Unlike a stationary signal (where properties like mean and autocorrelation are constant), a cyclostationary signal has properties that repeat with a fixed period. In the context of milling processes, the vibration signals recorded during the process are cyclostationary and this property can be utilized for further analysis. The period that dictates the cyclostationarity of a signal is usually the tooth passing period, or most commonly in processes with tool runout, the spindle rotation period [3.28]. A signal $x(t)$ is cyclostationary with period T_0 if:

1. The mean is periodic (first-order cyclostationarity)

$$E[x(t + T_0)] = E[x(t)]$$

2. The autocorrelation function is periodic (second-order cyclostationarity). The autocorrelation function is essentially the correlation of a signal with a version of the signal, shifted by the amount of τ .

$$R_x(t + T_0, \tau) = R_x(t, \tau)$$

$$\text{where } R_x(t, \tau) = E \left[x \left(t + \frac{\tau}{2} \right) x^* \left(t - \frac{\tau}{2} \right) \right]$$

To verify the cyclostationarity of the vibration signals recorded from the robot machining cell, the rolling mean and the autocorrelation are computed for different values of τ (stable and chatter cases). The results are presented below.

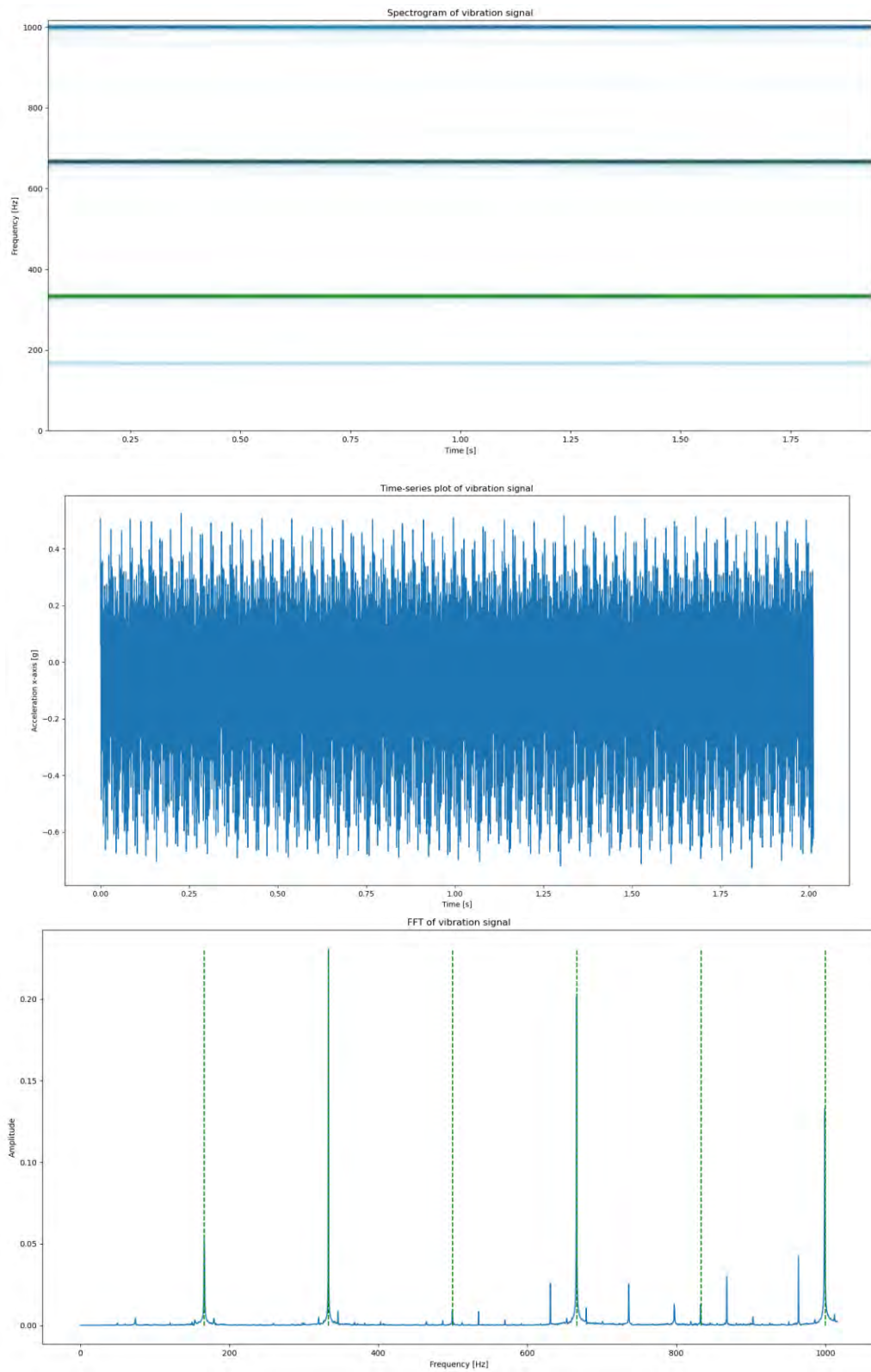
Stable machining case:

Figure 3.10 Spectrogram (top), time-series plot (middle) and FFT (bottom) of the vibration signal for a stable process – dashed lines in the FFT plot correspond to the spindle rotation frequency and its harmonics

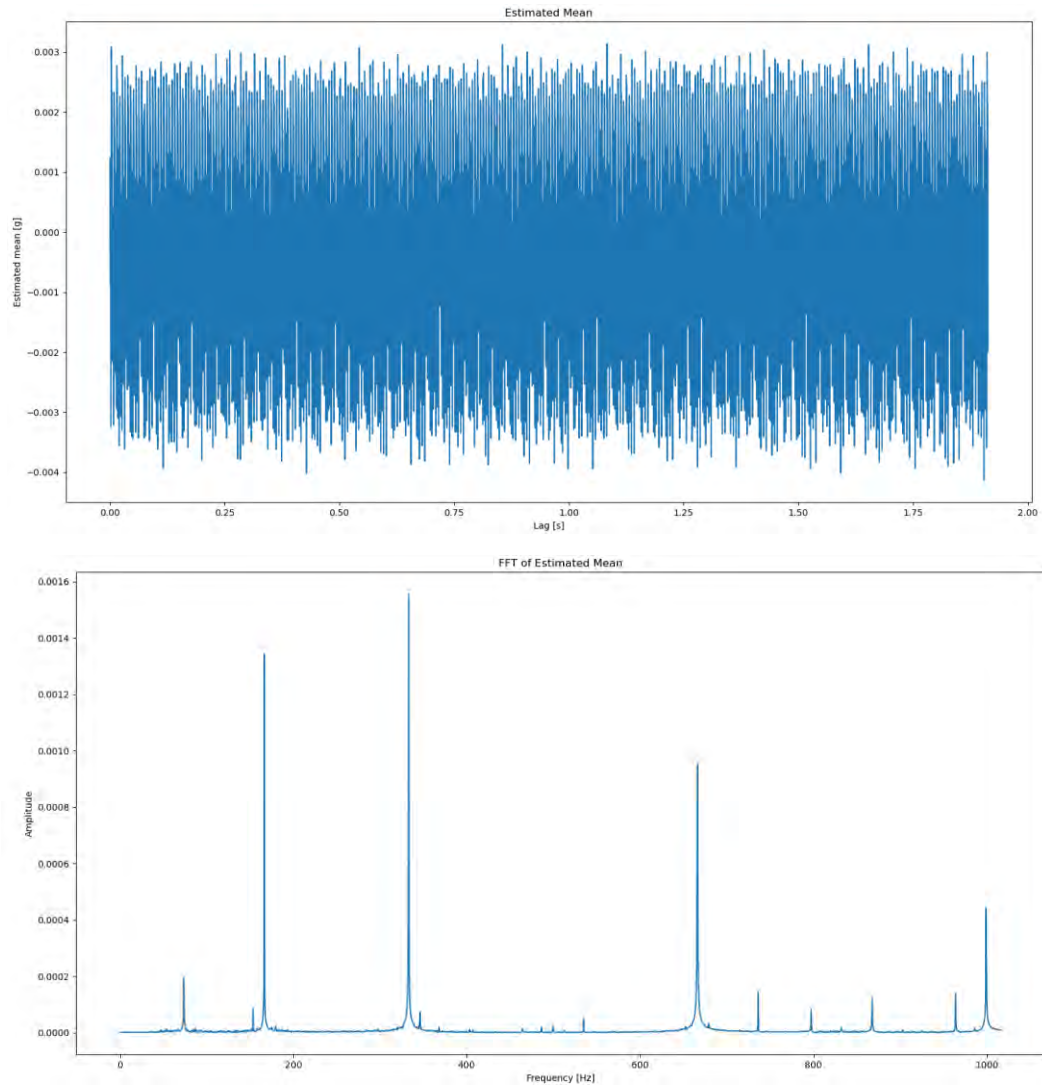


Figure 3.11 Time-series plot (top) and FFT (bottom) of the rolling mean of the vibration signal for a stable process

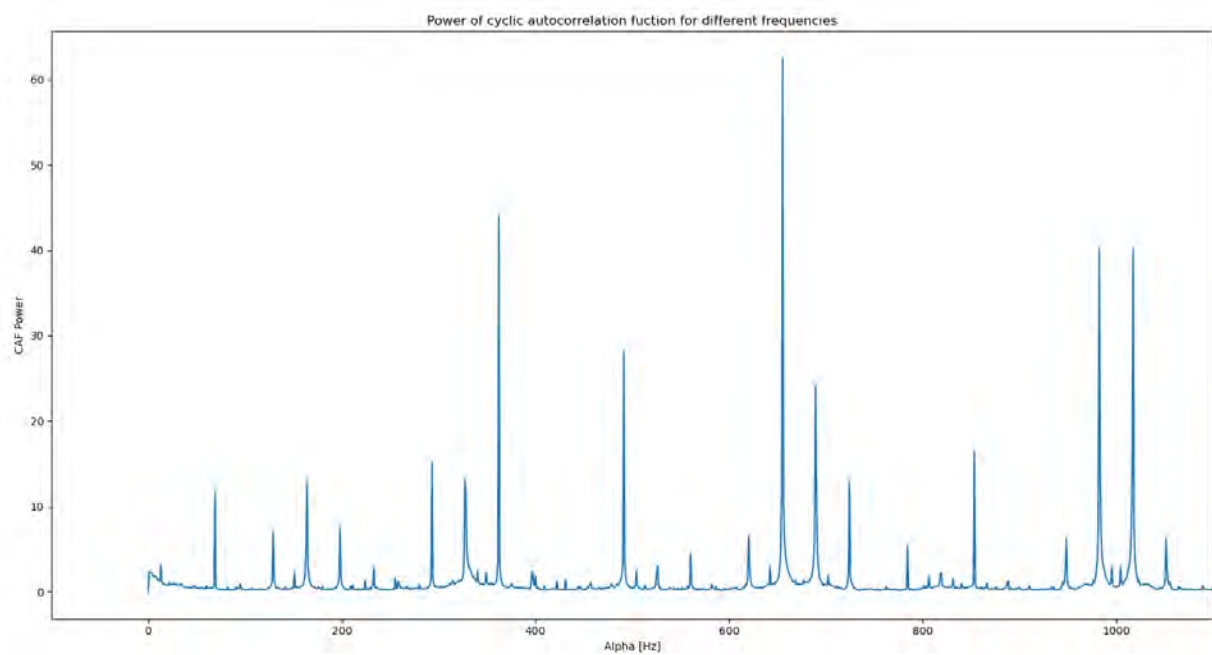


Figure 3.12 Power of cyclic autocorrelation for a stable process

Chatter case:

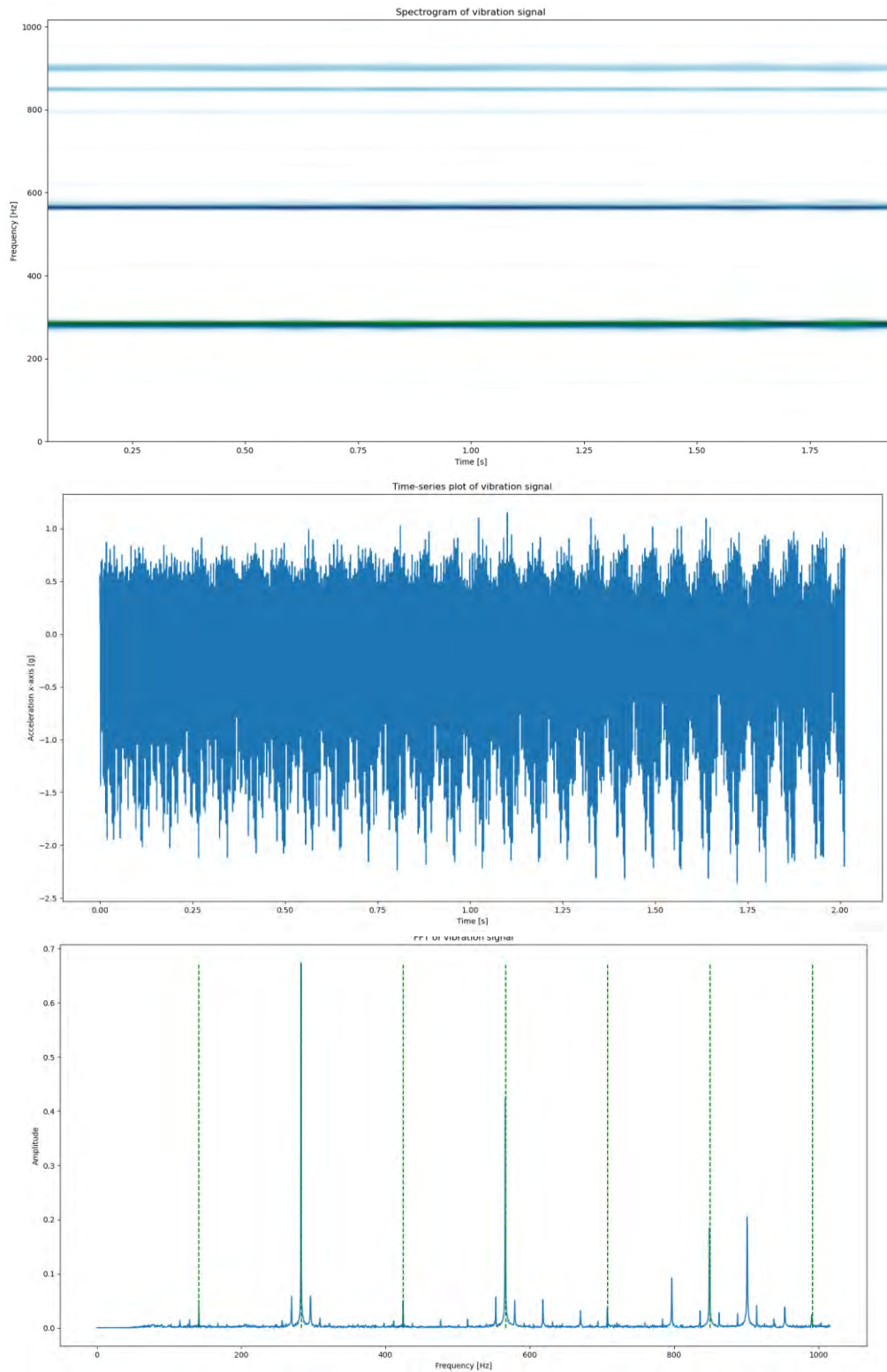


Figure 3.13 Spectrogram (top), time-series plot (middle) and FFT (bottom) of the vibration signal for an unstable process – dashed lines in the FFT plot correspond to the spindle rotation frequency and its harmonics

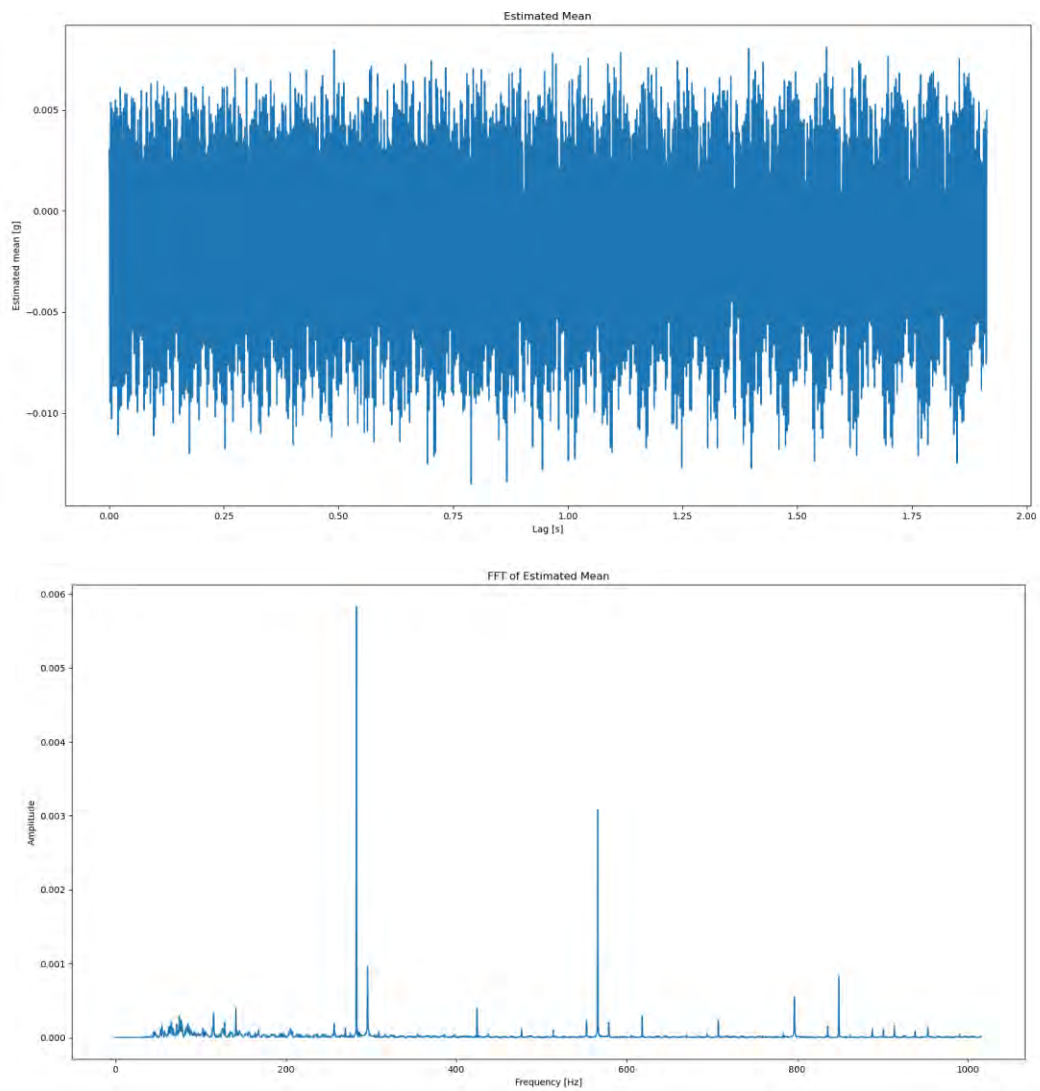


Figure 3.14 Time-series plot (top) and FFT (bottom) of the rolling mean of the vibration signal for an unstable process

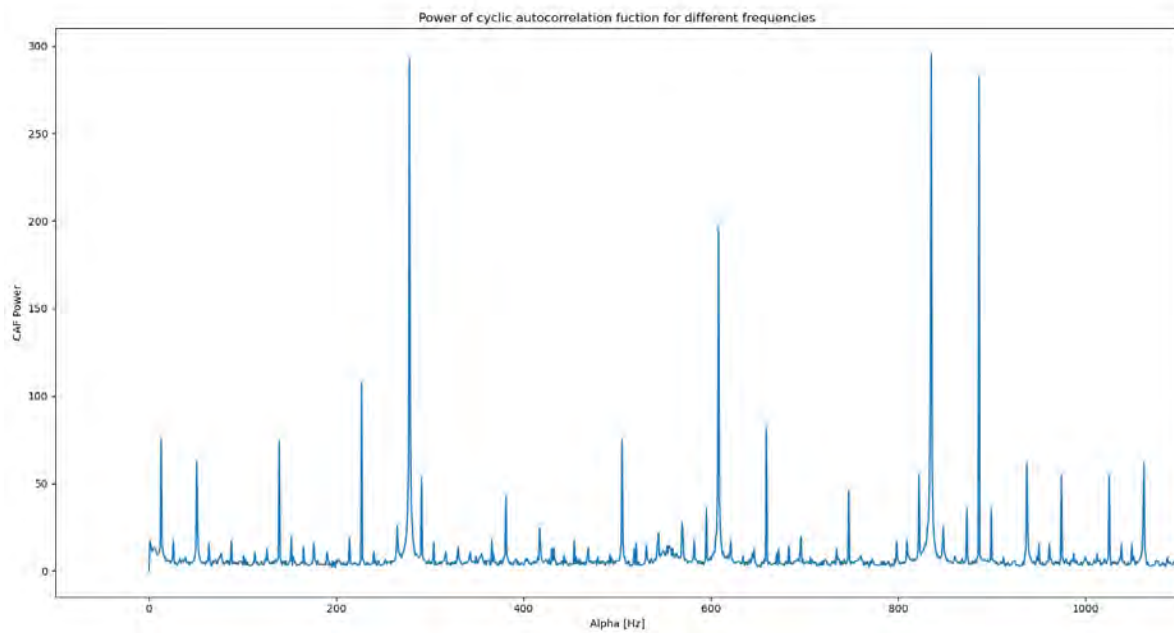


Figure 3.15 Power of cyclic autocorrelation for an unstable process

By examining Figure 3.10 to Figure 3.15, it is evident that both the rolling mean and the cyclic autocorrelation exhibit periodicity. This verifies the initial assumption that the signal is second-order cyclostationary and is in-line with what was expected, based on the examination of the available literature [3.28]. Another very interesting observation can be made by examining the plot of the vibration signal vs the spindle rotation angle. Figure 3.16 depicts the angular sampling for a stable case, while Figure 3.17 depicts the angular sampling for an unstable case. Multiple rotations are overlapping in the same plot. Angular sampling of the signal also verifies the cyclostationarity assumption. The stable signal is “tightly packed” and dominated by the spindle rotation frequency and its harmonics (again the tooth passing frequency is dominant). On the other hand, in the chatter signal the synchronous variance rises and cyclostationarity starts to break.

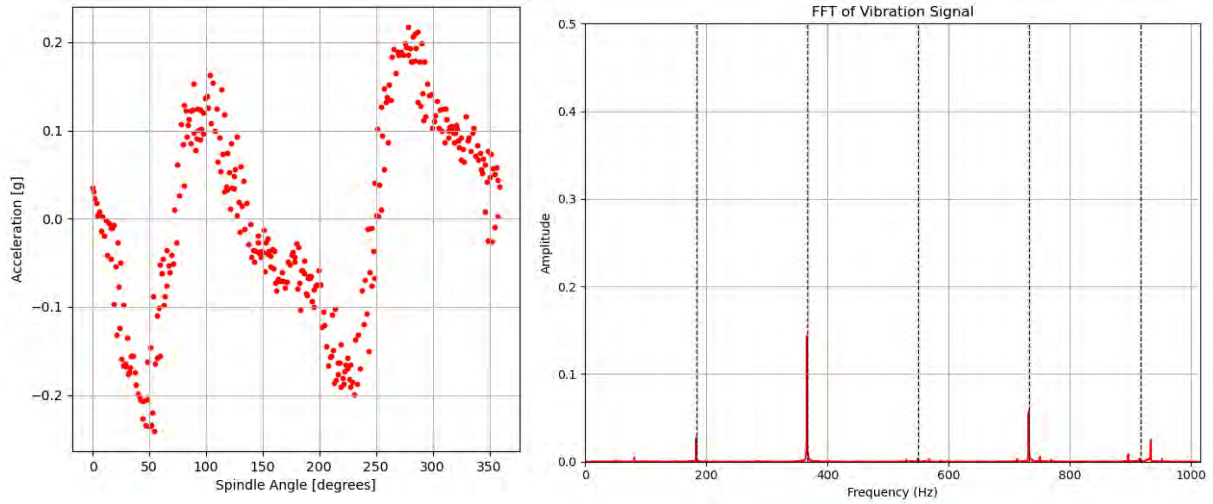


Figure 3.16 Angular sampling of a stable vibration signal

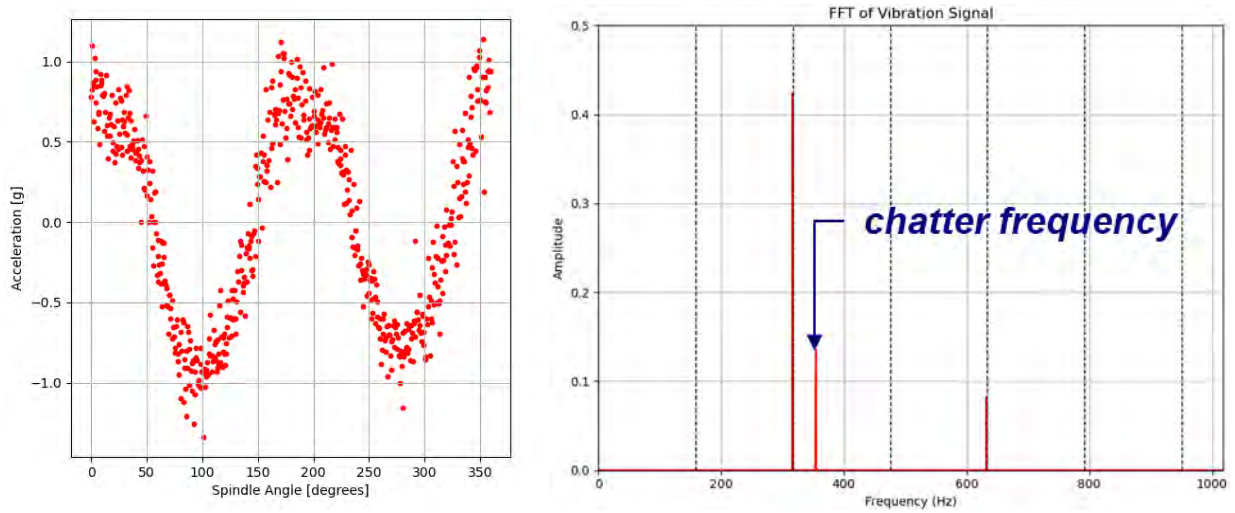


Figure 3.17 Angular sampling of an unstable vibration signal

So, the cyclostationarity feature that is calculated from the time domain representation of the signal is the synchronous variance, defined by the equation 3.4.

$$v_T^N(t) = \frac{1}{N} \sum_{k=0}^{N-1} x(\text{mod}(t + kT, NT) - m_T^N(t))^2 \quad (2) \quad (3.4)$$

where:

- N is the number of spindle revolutions in examined signal window
- $m_T^N(t)$ is the synchronous averaging given by the following equation

$$m_T^N(t) = \frac{1}{N} \sum_{k=0}^{N-1} x[\text{mod}(t + kT, NT)] \quad (3.5)$$

where $\text{mod}(a, b)$ is the remainder of the division of a and b . As it regards this feature, it is expected that the synchronous variance of the signal is going to be increased as the process transitions from stable machining to chatter.

In the end, the energy ratio and synchronous averaging are calculated for each axis of the vibration signal and are used as inputs for the machine learning model that is responsible for determining the presence of chatter in the process.

3.5. Machine Learning Approach

In order to train a machine learning model, a set of experiments needs to be conducted to get data from both stable and chatter situations. The goal of this experimental campaign is to get a balanced training dataset that is as diverse as possible. That means that chatter and stable datasets should be equally distributed as much as possible and that process parameters, robot poses, workpiece materials and cutting tools need to vary as much as possible. Simultaneously, the training dataset should be as small as possible without hindering the performance of the algorithm, requiring minimal resources to (re)train the algorithm, if necessary.

The workpiece materials that were processed were Aluminum 7075-T651 and 316L Stainless Steel. For the 316L case, the coupons that were used were manufactured through Additive Manufacturing (Laser Metal Deposition, as the robot cell also possesses AM capabilities). The cutting tools that were used were: (i) a Sandvik R390-016A16-11L indexable milling cutter with Sandvik R390-11 T3 04E-NL H13A cutting inserts for aluminium machining and Sandvik R390-11 T3 02E-PM 4340 for steel machining; (ii) a Sandvik R390-010A10-07L indexable milling cutter with Sandvik 390R-070202M-PM 4340 inserts for steel machining; (iii) a Gühring 4248 6.000 ball nose end mill.

The machining operations to generate the datasets were either side milling (with a staircase coupon) or ramp milling. For the former, flat coupons were used, where different process parameters were tested, while for the latter, ramp geometries were machined with ascending depth of cut (Figure 3.18). Especially the second type of coupons is helpful to exactly evaluate the chatter onset as the depth of cut reaches is critical limit for a specific set of spindle speed, feed per tooth and radial engagement.

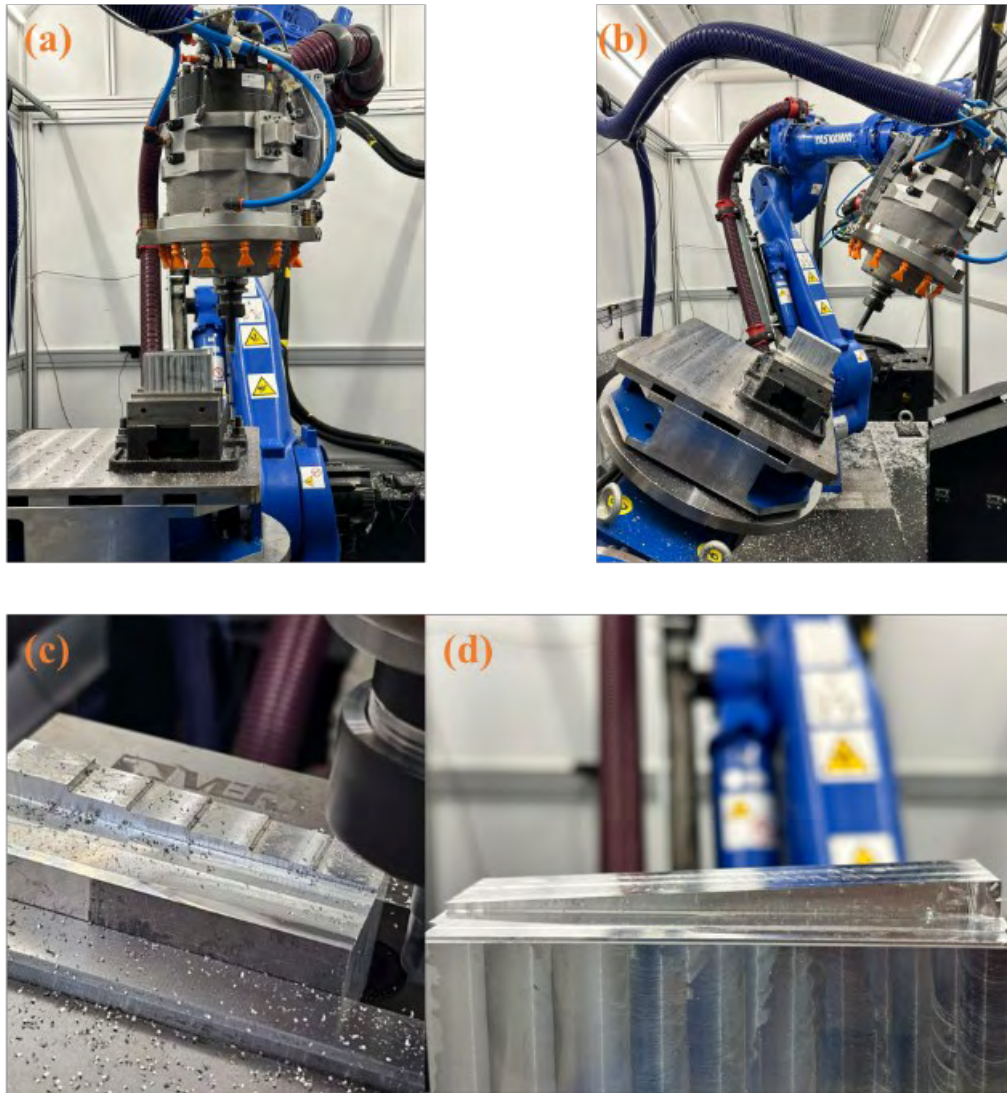


Figure 3.18 Variations between machining experiments: (a) upright pose; (b) inclined pose; (c) staircase coupon; (d) ramp coupon

A wide range of process parameters was tested for each one of the machined materials. These are outlined in Table 3.3. The robot poses were also varying between experiments, as depicted in Figure 3.18. The sampling frequency during the experiments was 10kHz. Window sampling was performed on the acquired data of each experiment with a window length of 4098 samples. In total, 64 experiments (i.e. 64 machining passes) were conducted to generate the dataset for the algorithm training. Using the window sampling that was mentioned above, 237 data points were generated for training.

Table 3.3 Process parameter ranges in the training dataset

Material	Spindle Speed [RPM]	Feed per Tooth [mm]	Axial Depth of Cut [mm]	Radial Depth of Cut [mm]
Aluminum	6000 – 11000	0.050 – 0.150	1 – 8	1.0 – 15.0
Stainless Steel	4000 - 12000	0.030 – 0.163	0 – 6	0.3 – 1.0

The next step is the selection of an appropriate AI model that will use the features extracted from the vibration signal to determine the presence of chatter. The problem that needs to be solved is a binary classification problem. This reduces the scope of applicable algorithms for this specific case, with typical, simpler machine learning and neural network architectures being the most appropriate. The following criteria are being considered in the selection of the model:

- **Real-time suitability:** The ability of the model to process the inputs and provide a response in a timely manner. This is an especially important criterion, as the model will be intended for real-time applications. In the context of chatter detection, real-time means that at least one chatter assessment per second should be performed [3.29].
- **Computational efficiency:** The required computational resources to train and, mainly, run the model. This criterion impacts the ability to deploy the model in existing hardware and the investment cost for implementing the chatter detection system, which dictates its scalability in real industrial settings.
- **Explainability:** The ability to interpret the decisions of the model. Explainability is a highly important criterion, since in a real environment, an AI algorithm might start making incorrect predictions after a large period of time, due to model drift or low-quality input data. The ability to easily track the decisions of the model helps engineers and operators to debug the system.
- **Robustness to noise:** The ability of the model to operate even with a level of noise in the input data, which is always present in real, industrial settings.
- **Training data requirements:** The volume of data needed to train the model. This is also an important criterion and is linked to the requirements set in Chapter 1, since, in real applications, the resources that a company can dedicate to train an AI model are very limited.
- **Generalization across conditions:** The ability of the model to maintain its performance across different milling conditions (machine tools, cutting tools, process parameters, workpiece materials, milling operations). This is also in line with the requirements set in Chapter 1 and it dictates the scalability of the system in real, industrial settings.

Table 3.4 presents a decision matrix table, where the criteria, along with weights that reflect their importance, are used to evaluate the most popular AI models that are used for classification. Support Vector Machines (SVM), Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN),

Random Forest (RF), k-Nearest Neighbors (KNN), Decision Trees (DT) and Logistic Regression (LR) are evaluated.

Table 3.4 Decision matrix table for selection of the chatter detection model

Criterion	Weight	SVM	ANN	CNN	RF	KNN	DT	LR
Real-time suitability	0.25	5	3	2	4	1	5	5
Computational efficiency	0.15	5	2	2	3	2	5	5
Explainability	0.15	5	2	2	3	2	5	5
Robustness to noise	0.15	4	3	4	5	2	3	3
Training data requirements	0.1	4	2	3	3	2	3	3
Generalization across conditions	0.1	4	4	4	3	2	2	3
Total score		4.55	2.80	2.80	3.55	1.75	3.90	4.10

SVMs offer very good performance in high-dimensional (i.e. large number of input features) datasets, where limited number of samples is available. They can use different kernels to address non-linear problems and are robust in terms of generalization and noise tolerance. Also, their simple architecture makes them well-explainable. ANNs are very powerful for detecting complex patterns in their dataset, but they require very high training time and large datasets, in order to avoid overfitting. Additionally, they are difficult to interpret. CNNs are more complex and more capable than ANNs, due to their architecture in the hidden layers. They are excellent at learning spatial or temporal features, especially from time-frequency representations of vibration signals, such as spectrograms or wavelet transforms. However, they need even larger datasets than ANNs, in order to avoid overfitting. Moreover, the forward passes of the input features through convolution layers and pooling add latency. In order to use them in real-time applications powerful, specialized hardware (e.g. FPGA) is usually required to meet the desired response times. Decision Trees are fast and offer the best explainability. They are not as robust in high-dimensional spaces and sometimes tend to overfit, unless they are used in an ensemble (i.e. a Random Forest). Random Forests are an evolution of DTs and offer also good accuracy and noise robustness. However, they can be slower during inference if ensemble size is large. KNNs have a very simple architecture, but they have poor real-time performance and are very sensitive to noise. Finally, LR is also highly explainable but it may underperform in complex or nonlinear classification problems. As a result, SVM is considered as the best trade-off between real-time suitability, classification performance and explainability and will be

used for chatter detection. The working principle of SVM is that it tries to construct a hyperplane that separates the two classes in the dataset, while maximizing the margin between the classes and the hyperplane. The margin is defined as the distance between the data point closest to the hyperplane for each class. The hyperplane has a dimension of $n-1$, where n is the length of the feature vector (i.e. number of features in the input dataset). Figure 3.19 shows how different hyperplanes can be constructed. In a two-dimensional feature vector, the hyperplane is just a line. It is evident in Figure 3.19 that all three hyperplanes (H1, H2 and H3) separate the two classes but H1 is the one maximizing the margin.

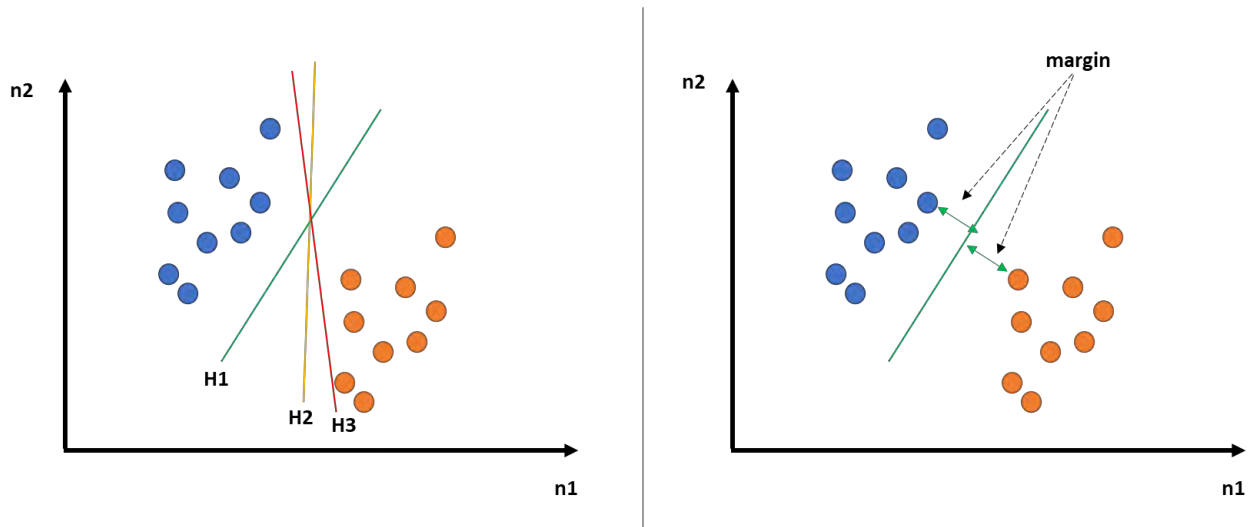


Figure 3.19 Possibility of different hyperplanes for separation of the dataset [3.7]

The margin shown in Figure 3.19 is a hard margin. This means that the model is not allowed to misclassify any data point during the training phase. Defining a hard margin assumes that there are no outliers in the dataset, which is never the case with real, industrial data. To address this, a soft margin can be introduced to the algorithm. This means that some misclassification is allowed during the construction of the hyperplane, if the algorithm performs better in the rest of the training dataset. This enables the algorithm to become less sensitive to noise and generalize better across different conditions. The slack variable, ξ , is introduced when training with a soft margin, which dictates how far from the hyperplane can a misclassified data point lie (Figure 3.20). The magnitude of the slack variable is controlled by the variable C , which is a hyperparameter of the SVM algorithm

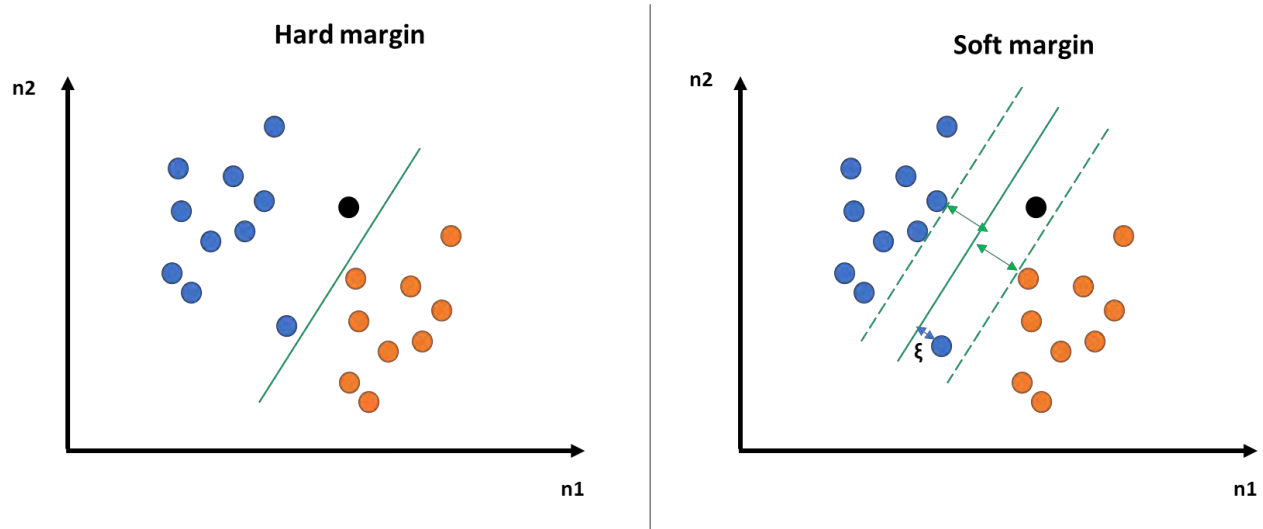


Figure 3.20 Comparison of a hard vs soft margin in SVM training [3.7]

When the dataset is not linearly separable, SVM can handle non-linearities, through the use of kernel functions, since the hyperplanes that are constructed can only be linear. The kernel functions allow the computations related to the hyperplane construction to take place in a higher dimension. The kernel does not actually transform the data in a higher dimension; it just explores their higher-dimensional, non-linear relationships. This ensures that the computational cost is minimally increased. The most widely used kernel functions are polynomial, Gaussian, radial basis function (RBF) and sigmoid. Figure 3.21 how kernel functions can transform datasets that are non-linearly separable into a higher dimensional space and help in the construction of the hyperplane.

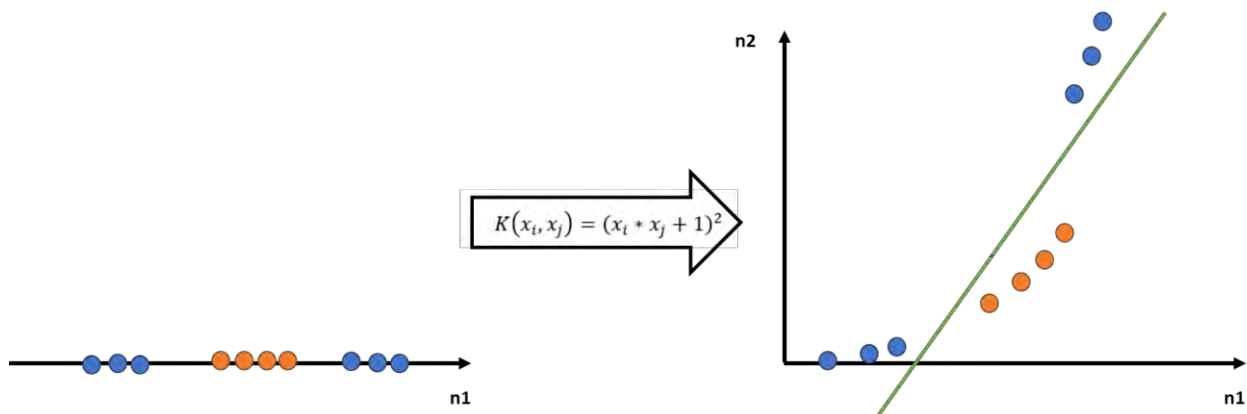


Figure 3.21 Use of kernel functions to map data into a higher dimensional space [3.7]

3.6. Software Implementation

In order to train the SVM model, as well as deploy it for real-time operation, a Python software has been developed. The LJM package of Labjack has been utilized, which offers APIs for configuring and controlling the Labjack T8 DAQ. Streaming of vibration data was handled from the LJM package. The

SVM model has been trained and deployed, using the popular scikit-learn package of Python [3.30]. The connection with the robot controller to retrieve position and spindle speed data is achieved through a custom Python class that implements the High Speed Ethernet Protocol of Yaskawa. Since the vibration data sampling rate is 10kHz, while the sampling interval for communication with the robot controller is limited at 40ms, by the hardware of the controller, the Python software timestamps and synchronizes the two data streams. So, a vibration data packet and chatter status is assigned for each position that is recorded from the robot controller. Since this is interesting mainly for offline analysis, it is still possible to utilize these data, by calculating statistical metrics (e.g. mean vibration amplitude in the data packet) and correlating them with the position of the robot, process parameters, etc. The data are logged in a .csv file. In order to strengthen the usability of the software and make it also relevant for offline analysis by process planners, apart from monitoring, the software has also been interfaced with the CAM. Most CAM software allow the user to export the machining operations that they have programmed within the software in some type of neutral format (usually .XML). The exported data include the type and name of operation, the cutting tool geometry and the process parameters used. Toolpath data are not included, as they are only exported in the part program in machine-specific language. The chatter monitoring is able to parse the file that contains these data and enable the operator to select the machining operation that takes place, when a vibration signal and chatter status are recorded. A header is added to the log file that contains the machining operation information. This helps in offline analysis of the data and link with the downstream process (e.g. quality assessment). The user can also manually configure a process from the user interface of the software. The software has been configured to automatically parse such files from SprutCAM and hyperMILL. Finally, a user interface has been developed that allows the operator to interact with the software and get information regarding the status of the process. Figure 3.22 shows the dashboard page, which is the main page used for the real-time operation. The operator can visualize the time-series and FFT of the vibration signal, the chatter status, as well as some pre-calculated metrics (vibration intensity and instability) that can be used to get an overview of the process even as a non-expert, who cannot analyze the time-series and FFT. The operator can select the current operation, based on the ones configured in the process setup page. Also, they can assign manual labels regarding the chatter status based on their experience. These manual labels are also included in the log file and can help in validating potential deterioration of the performance of the algorithm, but, most importantly, in efficiently creating new datasets for model training, if necessary. Figure 3.23 depicts the process setup page, where the user can automatically parse neutral format files from SprutCAM or hyperMILL or setup their own custom operations. Figure 3.24 depicts the settings page, where the user can configure settings regarding the sensor (calibration values), DAQ (sampling rate, channels to record) and SVM model version that should be used for chatter detection. Figure 3.25 showcases the offline analysis page, where the user can open and analyze logs in the time and frequency domains.

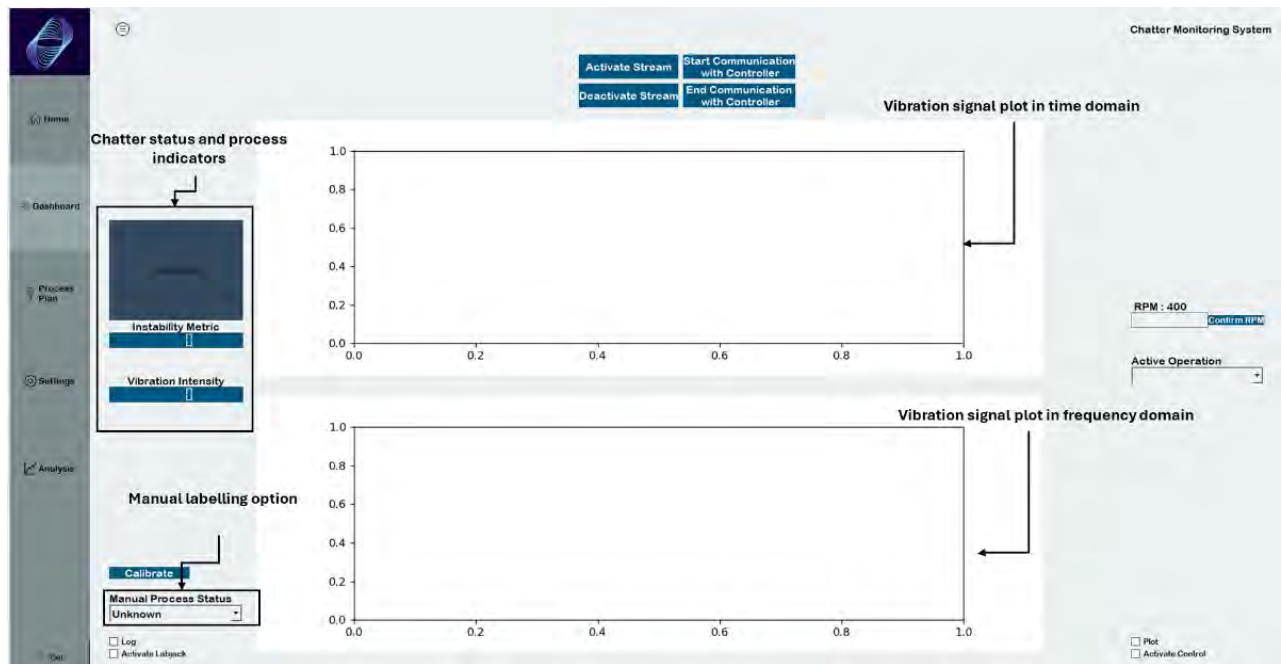


Figure 3.22 Dashboard page of chatter monitoring software

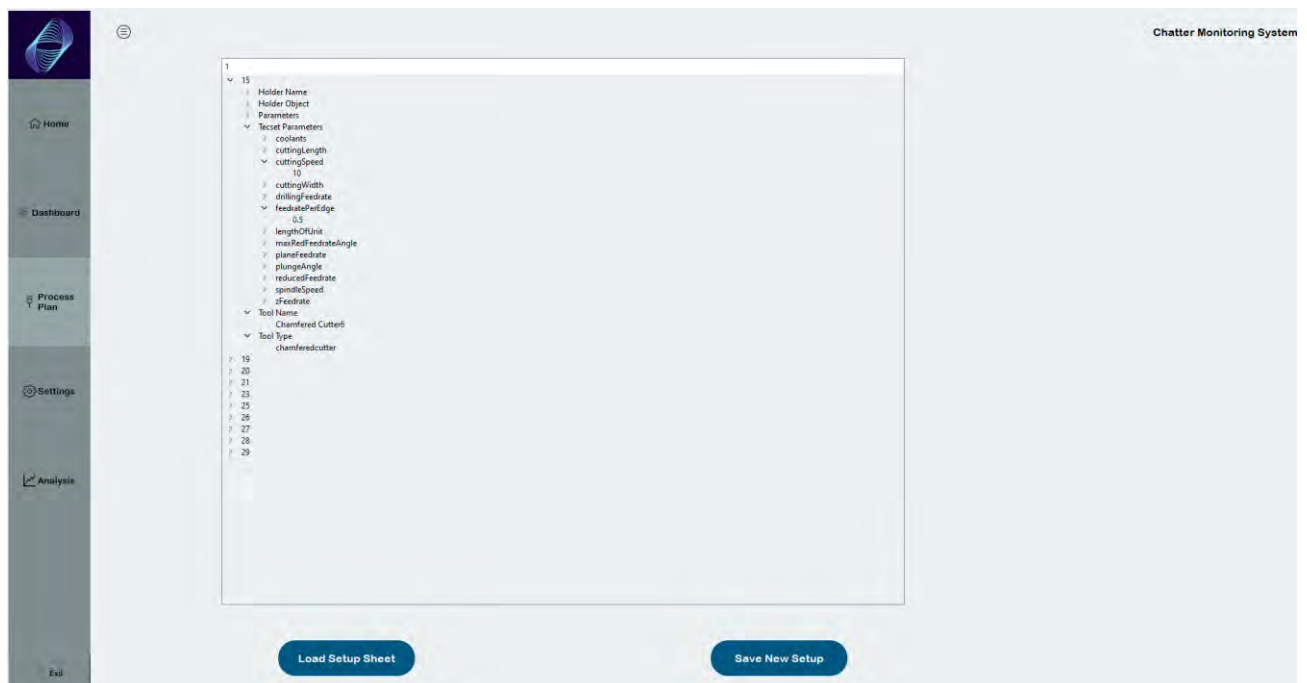


Figure 3.23 Process setup page of chatter monitoring software

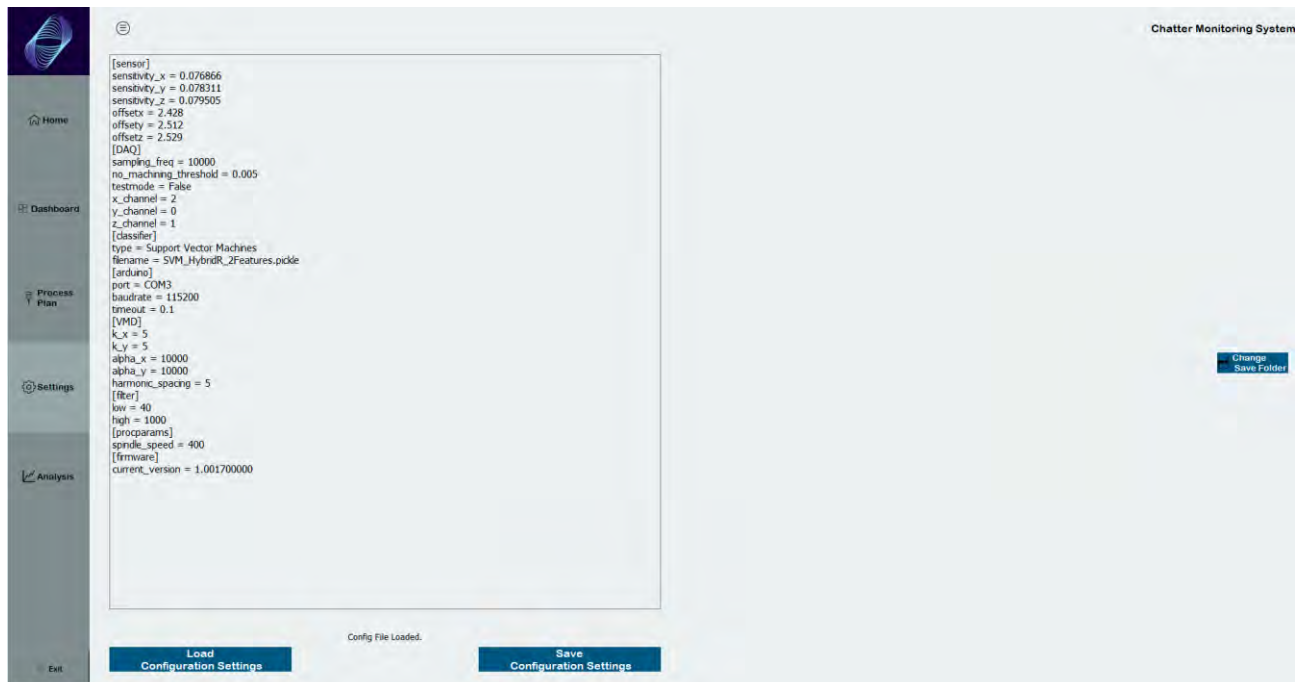


Figure 3.24 Settings page of chatter monitoring software



Figure 3.25 Data analysis page of chatter monitoring software

3.7. Performance Evaluation and Generalisation

The features that have been presented in section 3.4 have been calculated for the 237 data points and fed to the SVM algorithm. 70% of the data points were used for training, while 30% was used

for testing. After tuning the hyperparameters of the SVM, through exhaustive grid search optimization, the final hyperparameters were concluded as follows. The kernel function was Radial Basis Function, parameter $C = 700$ and $\gamma = 1.8732$. The criterion that was used for tuning the hyperparameters was the Area under the Receiver Operating Characteristic curve (ROC AUC Score). Thanks to the careful feature engineering, a great performance has been achieved by the SVM as it is presented in Figure 3.26 and Figure 3.27.

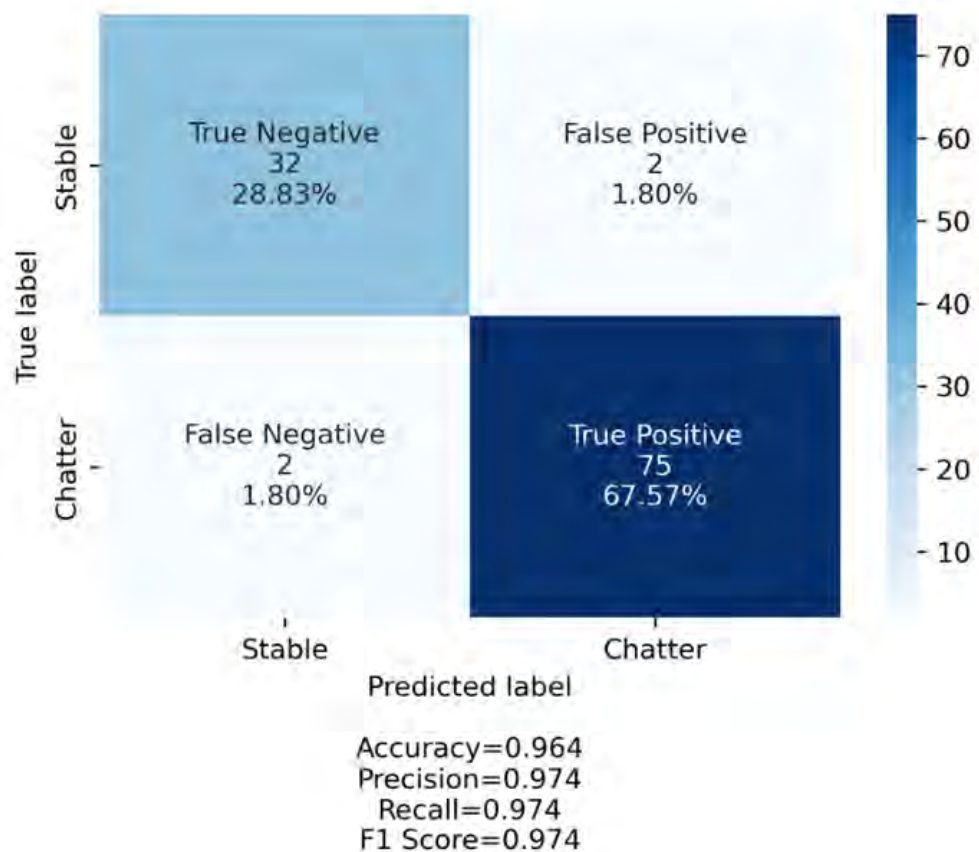


Figure 3.26 Confusion matrix of the SVM classifier

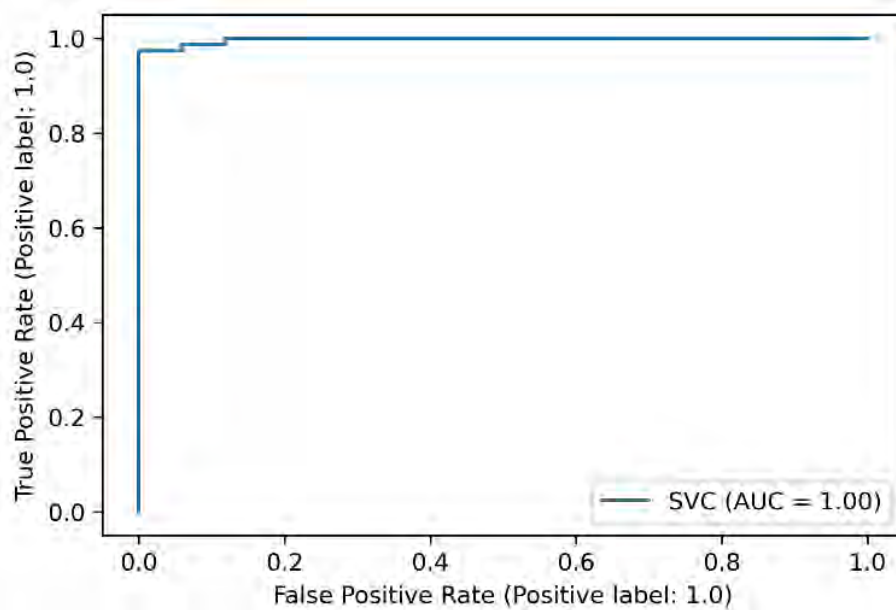


Figure 3.27 ROC AUC curve of the SVM classifier

In order to test the ability of the approach to generalize in other machining conditions and also test if it can be transferred also to CNC machining centers, the chatter detection system has been deployed in four additional machine tools:

- An XYZ SMX SLV vertical milling machine, in which the sensor has been integrated on the machining vice. This machine is also part of the equipment of the machine shop of the Laboratory for Manufacturing Systems and Automation.
- A Mazak vertical CNC machining center, in which the sensor has been integrated on the machining vice. This machine is owned by a manufacturing company in the Netherlands and is operating on heavy-duty machining cases, where stainless steel is machined with high material removal rates.
- A HAAS Mini Mill vertical CNC machining center, in which the sensor has been integrated on the machining vice. This machine is owned by a manufacturing company in Athens, Greece
- A HAAS VF2-SS CNC vertical, in which the sensor has been integrated on the spindle head. This machine is owned by a manufacturing company in Athens, Greece and is a high-stiffness machining center, with different dynamics than the other installations. The usage of this machine focuses on high-precision manufacturing of, mainly aluminum, components.

The system was directly installed in the machine tools, and the approach was tested without retraining the algorithm, with the performance on chatter detection being unaffected. It is important to note here that three out of four additional integrations took place in real, industrial settings, which also strengthens the claim of industrial suitability.

While not in the direct scope of this work, it is interesting to mention that in the case of integration on the HAAS VF2-SS, the algorithm has also been used in a non-conventional setup of distributed

monitoring with 5G. The sensor and DAQ fed data to a low-cost edge device (Raspberry Pi), which transmitted them through 5G and MQTT to a server hosting a containerized application of the chatter detection algorithm. The edge device was installed in Athens, Greece, while the server hosting the algorithm was placed in the premises of the Laboratory for Manufacturing Systems and Automation in Patras, Greece. Even in this case, the whole approach could be effectively utilized thank to the low computational demands. The interested readers can find more details on that topic in [3.31].

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4. CHAPTER 4. IN-PROCESS PREDICTION OF THE TOOL WEAR LEVEL

4.1. Tool Wear Mechanisms in Milling

Tool wear is the phenomenon of the gradual deterioration of the cutting tool. There are several physical mechanisms that may occur individually or simultaneously. They can be categorized in abrasion, adhesion and diffusion wear.

- Abrasion takes place because as the chips are generated from the workpiece, smaller particles of the cutting tool are also being removed. These particles are caught in the tool-chip interface causing additional abrasion wear. Also, the workpiece material might contain or form carbides, oxides and nitrides during the cutting process, which also cause abrasion wear.
- Adhesion is a result of the surface pressure during the relative motion between the cutting tool and the chip. As the (softer) chip is generated, it might adhere to the (harder) cutting tool. The adhered material is unstable and might tear small fragments from the cutting tool as it is peeled away from a successive chip. A typical example of adhesion wear is the built-up edge (BUE), where the chip material welds to the cutting edge. BUE usually takes place when soft, ductile materials (e.g. aluminum) are machined in low cutting speeds.
- Diffusion refers to the exchange of atoms between the workpiece and cutting tool material. When the temperature at the tool chip interface rises to a significant level, the atoms in the two become restive and migrate to the opposite material where the concentration of the same atom is lower. For example, when a tungsten carbide (WC) cutting tool is used to machine a steel workpiece, the carbon atoms of the cutting tool diffuse to the moving steel chips, which have a lower concentration of these atoms.

Based on these three physical mechanisms, different types of wear can take place at the different locations on the cutting tool. Table 4.1 and Figure 4.1 provide an overview of the main tool wear types in milling, the physical mechanisms that govern them and the locations on the cutting tool that each wear type is exhibited. Among those, flank wear is the main wear mechanism that is observed in almost all milling operations, while the others can appear in the cutting tool, either due to specific properties of the workpiece material, cooling medium selected or process parameters, with different frequencies of appearance.

Table 4.1 Overview of the wear types in milling

Wear type	Location	Mechanism/Cause
Flank wear	Flank face	Abrasion, diffusion
Crater wear	Rake face	Diffusion, high-temperature abrasion
Built-up edge	Cutting edge	Adhesion
Edge chipping	Nose / edge corner	Workpiece instability, vibrations
Thermal cracks	Edge corner	Thermal fatigue from thermal cycling
Plastic deformation	Edge / nose	Thermal softening
Notch wear	Depth of cut line	Adhesion, abrasion
Chip hammering	Edge corner	Poor chip breakage/evacuation
Edge breakage	Nose	Mechanical overload

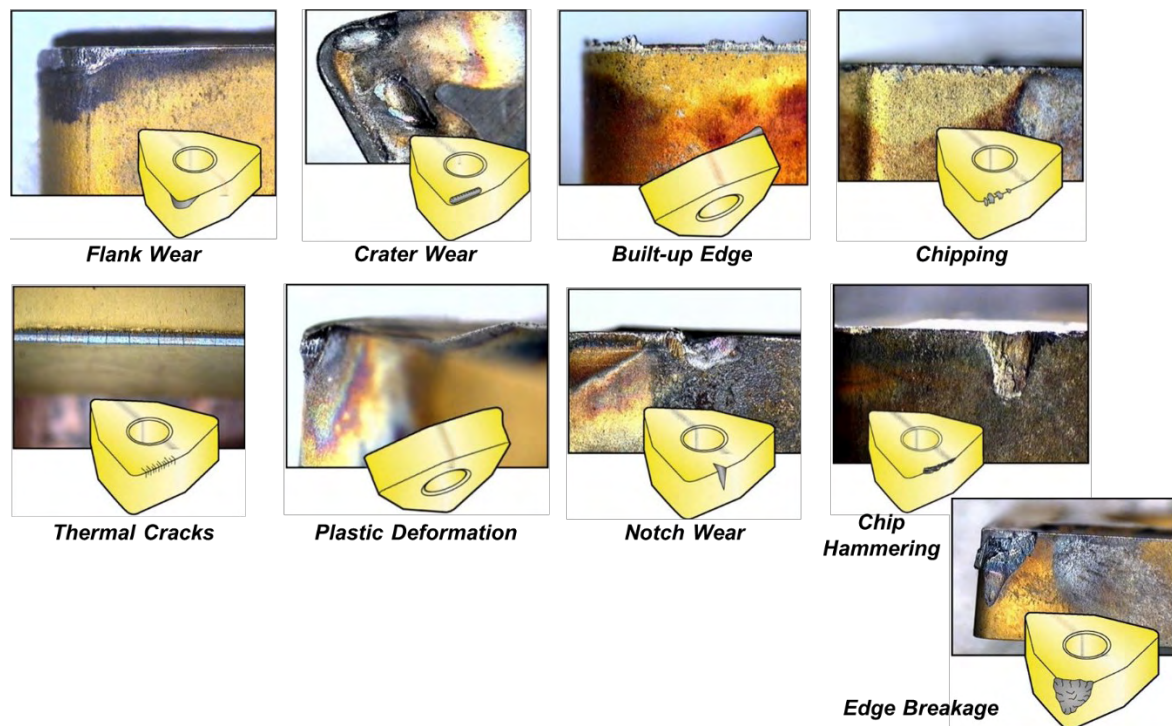


Figure 4.1 Main tool wear types in milling [4.1]

Tool wear is a phenomenon that is always present in the milling process and cannot be avoided. However, it can be managed efficiently, so that the negative impact on the process is minimized. Essentially, the goal is to be able to use the most out of the available service life of the cutting tool and replace it just on time before breakage occurs that might result in a scrapped part. Additionally, in high-precision machining applications, tool wear will reduce the effective cutting diameter of the cutting tool. This needs to be compensated for, through appropriate radial compensation in the G-Code. Moreover, by linking the selection of process parameters and tool wear evolution, it is possible to make informed trade-offs between productivity and tool wear rate, which directly translates to financial benefits. As such, systems for monitoring tool wear can have a lot of apparent, immediate benefits in a machining company, so they are one of the main aspects that can be addressed through digitalization. As mentioned in Chapter 1, industrial demands call for systems that are Plug & Produce, robust and reconfigurable. This reduces the barrier for industrial adoption, in terms of expertise and cost required to implement such technologies in a real production scenario. Ultimately, this drives research for better monitoring systems that can address these industrial demands. On that front, advanced signal processing techniques and Artificial Intelligence come as key enabling technologies [4.2].

On top of that, sensor technology has also advanced significantly and can play a role in creating systems that adhere to the Plug & Produce principles and can provide higher quality data than what has been available up to now. Specifically, miniaturization of sensing elements and electronics has enabled the development of sensor-integrated tooling systems. In the context of machining processes, such systems usually refer to the integration of sensing elements on the cutting tool (end mill or indexable milling head) [4.3], tool holder [4.4] or machining vice [4.5]. Especially in the context of milling, the ability of wireless data transmission with a high throughput and minimal data loss is crucial for the integration of sensors in rotating elements [4.6]. The key advantages of sensor-integrated tooling are that they can measure process-related data as close to the process as possible, and they require no intervention to the machine tool itself. The latter can be considered their biggest strength regarding the reduction of barrier for industrial adoption and also makes them easily transferrable between different machine tools. That means that a single sensor-integrated tool can be shared by many machine tools, only for critical operations, thereby minimizing investment cost.

Focusing on tool condition monitoring there have been numerous approaches presented in literature, utilizing conventional monitoring systems or sensor-integrated tooling systems as data sources. Starting from the detection of tool breakage [4.7] as an application of tool condition monitoring, research has evolved and is now proposing advanced systems that can estimate the actual wear level of the tool and the remaining useful life [4.8]. The data sources range from acoustic emissions[4.7], vibrations [4.9], cutting forces [4.10], current or power measurements in the spindle [4.11] or even in-line visual inspection of the cutting tool in the machine tool [4.12]. The latter can guarantee the accuracy of the measurement and the exact evaluation of tool condition, being a direct measurement method, but requires interruption of the process, which is a significant

drawback. Also, the environment of a machine tool, which includes chips and coolants, can make the integration of such a vision system challenging. For the rest of the data sources, which are indirect ones, the consensus in literature is that cutting force is the data source, where information related to tool condition can be easily extracted [4.13]. Signal power and current measurements are also useful data sources that can be linked with tool wear. It is a common understanding that the current drawn by the spindle motor is directly linked to the cutting torque, albeit not always linearly. Careful modelling of the transfer function between the spindle current and cutting force is required to create meaningful information from the current measurements [4.14]. This can complicate the transferability of systems based on spindle current or power measurements between different machine tools. On the other hand, acoustic emission and vibration measurements can be linked with tool condition. Especially acoustic emissions can be well linked with tool breakage in micro-milling applications [4.7]. However, because vibration and acoustic emissions are also dependent on other process-related phenomena, decoupling the tool condition information can be a significant challenge [4.9].

In the final pillar of this research, an approach for tool condition monitoring in milling is developed, utilizing cutting force and temperature measurements from sensor-integrated indexable milling head. These measurements are utilized to create a system comprised of a regressor and a multi-class classifier, enabling the estimation of both the flank wear level, as well as the tool status in the wear curve (break-in, steady-state wear, accelerated wear towards the end of life). The approach is directly retrofittable, since the sensor-integrated milling head is installed on the spindle through standardized mechanical interfaces and is validated regarding its generalizability in different machining conditions.

4.2. State of the Art in Tool Wear Monitoring in Milling

Advancing tool condition monitoring in milling is a core topic of research around machining for several decades. In this literature review, the most recent research advancements on the topic are presented, focusing mainly on the industrialization of tool condition monitoring, as well as the potential of Artificial Intelligence to contribute towards this purpose.

Cutting forces are rich in information related to tool wear and therefore are preferred by many researchers as the data source to develop a tool condition monitoring algorithm. Li and Liu [4.15] worked on the development of a tool condition monitoring system that enables the prediction of the remaining useful life of the cutting tool with a certain probability, utilizing hidden Markov models. A Kistler cutting force dynamometer was used as a data source and the process parameters and machining time were integrated as inputs in the model to enhance its adaptability. Nouri et al. [4.16] proposed a methodology for tool condition monitoring based on the cutting force coefficients. They proposed a wear indicator based on the cutting force coefficients, which can be tracked during the machining operation, utilizing cutting force data from a table dynamometer and cutting

conditions information. By calculating statistical features they were able to track out of control points that hint towards increased wear rate. The cutting force coefficients were used also by Pan et al. [4.17] for tool wear monitoring based on cutting force signals. By calculating the instantaneous milling force coefficients and using principal component analysis, they generated features that were used as inputs to a Support Vector Machine (SVM) model for wear state classification, between steady state wear and accelerated wear towards tool failure. Zhou et al. [4.18] utilized a cutting force singularity analysis approach. By extracting the Hölder exponents of cutting force signals and then calculating a set of statistical features from these exponents, they were able to use them as inputs to a SVM model for wear level prediction. SVM is a popular algorithm in machining monitoring applications, due to its simplicity in training and low computational cost, which facilitates deployment. However, SVM tends to have limitations. To address this, Kong et al. [4.19] proposed an improved SVM model that also integrates the whale optimization algorithm (WOA). Additionally, they used the neighborhood preserving embedding (NPE) to fuse the features extracted from the cutting force signal and reduce their dimensionality. They presented a significant reduction in modelling time-consumption (more than 30%) with comparable accuracy levels, compared to other commonly used SVM implementations. In another work focused on machining of compacted graphite iron (CGI), Xu et al. [4.20] proposed an adaptive neuro fuzzy inference system (ANFIS) to estimate tool wear, which was learned by the particle swarm optimization (PSO) algorithm. Apart from being able to perform real-time tool wear monitoring, their model could propose optimal process parameters, with the goal of prolonging tool life. Deep learning models have also been developed for tool wear monitoring applications based on cutting force signals. Cheng et al. [4.21] proposed a parallel convolutional neural network (CNN) architecture, with feature normalization to consider the effect of process parameters on tool wear. They managed to achieve higher calculation efficiency and better accuracy than traditional encoder-decoder models that can be found in literature.

Vibration data is also a popular data source for tool condition monitoring, because, despite the challenges related to decoupling the tool wear information from the signal, vibration sensors are generally a lower cost alternative compared to cutting force sensors, especially when MEMS accelerometers are utilized. The most effective method of analysis of the vibration signal is in the frequency or time-frequency domains, since disruptions or transient effects in the process can be effectively captured within the changes in the spectral content of a signal. Hesser and Markert [4.22] used a vibration sensing system mounted on the machining vice and trained a tool wear prediction model based on envelope analysis of the vibration signal and artificial neural networks. The main limitation of their approach is that the model is trained and tested on constant machining parameters. Mohanraj et al. [4.23] applied wavelet decomposition on the vibration signals and by using the wavelet coefficients, statistical features of the signal in the time domain and the Hölder exponents as input features, along with PCA for dimensionality reduction, they tested several Machine Learning models and neural networks, to compare their performance on wear level

classification. They concluded that the wavelet features and the Hölder exponents perform better as input features compared to the statistical features. Wavelet decomposition and extraction of wavelet features was also utilized by Wang et al. [4.24] who also applied the locality preserving projection for dimensionality reduction of the input features, which were then fed to an SVM model for wear level classification. The SVM is one of the most popular algorithms also in the case when vibration data are used for tool wear detection, due to its simplicity in training and deployment. Zhou et al. [4.25] designed a wireless, sensor integrated tool holder, by integrating a sensor ring, which incorporated a commercial vibration sensor and electronics for data acquisition and wireless transmission. By performing singularity analysis of the vibration signal they were able to extract features that were used to train an SVM model for wear level classification. Deep learning applications can also be found in literature, utilizing vibration signals as input. Xie et al. [4.26] proposed a digital twin for tool condition monitoring, which utilized long short-term memory recurrent neural networks (LSTM-RNN). Using this approach, they managed to improve the classification accuracy significantly, compared to SVM and simple RNN models, for the same dataset. A significant issue when considering vibration data as input for tool wear monitoring is the phenomenon of chatter. The existence of chatter can skew the predictions of the tool condition monitoring system. To address this, Lamraoui et al. [4.27] proposed a cyclostationarity approach for parallel chatter and tool wear monitoring. Cyclostationarity examines a signal, considering also its periodicity. Utilizing different features extracted from the cyclostationarity analysis, they were able to identify those that correlate with the phenomenon of chatter and the severity of tool wear.

It is evident that numerous studies have been presented, trying to address the problem of tool wear in milling, using very diverse approaches. Some methods, utilize indicators that have physical meaning and are based on the machining theory, such as the cutting force coefficients and the instantaneous wear modelling, but do not move forward to further automation of the decision-making process, which is critical for industrial implementation. Other studies, utilize statistical features, dimensionality reduction or non-diverse datasets for training of AI-based systems, which limits transferability within industrial applications. This study aims to bridge these two approaches and fill the gap by formulating features that incorporate the influence of process parameters and are derived from a broad spectrum of machining conditions, thereby enhancing the adaptability and generalizability of the AI-based tool wear model.

4.3. Description of the Measurement Setup

The instrumented milling head is a prototype that has been developed in the context of the EIT Manufacturing project, InToFlex [4.28]. It is a collaborative work between Walter AG, the Institute of Production Engineering and Photonic Technologies of TU Wien and myTool IT GmbH. The development of the instrumented milling head is outside the scope of its work. The overall development, calibration and verification of data quality has been carried out by Walter, TU Wien

and myTool IT GmbH. However, a brief description of the instrumented milling head is presented in this section for the sake of completeness. The instrumented milling head is based on a commercial Walter F2010.B.125.Z08.12.R752M milling head. Table 4.2 presents its specifications. The milling head was customized to enable cutting force, cutting temperature and vibration measurement. Piezoelectric sensors and thermocouples are integrated in the insert seats, which have been machined to accept sensorization. Additionally, in the machine adapter side, the electronics and vibration sensor are integrated. The triaxial accelerometer is directly mounted on the printed circuit board assembly (PCBA) of the instrumented milling head. This PCBA integrates also the charge amplifiers for the piezoelectric sensors. Digitization of the measurements takes place in the milling head. The PCBA is also equipped with a charging port. The whole PCBA is molded in the machine adapter side of the milling head using epoxy resin (Figure 4.2).

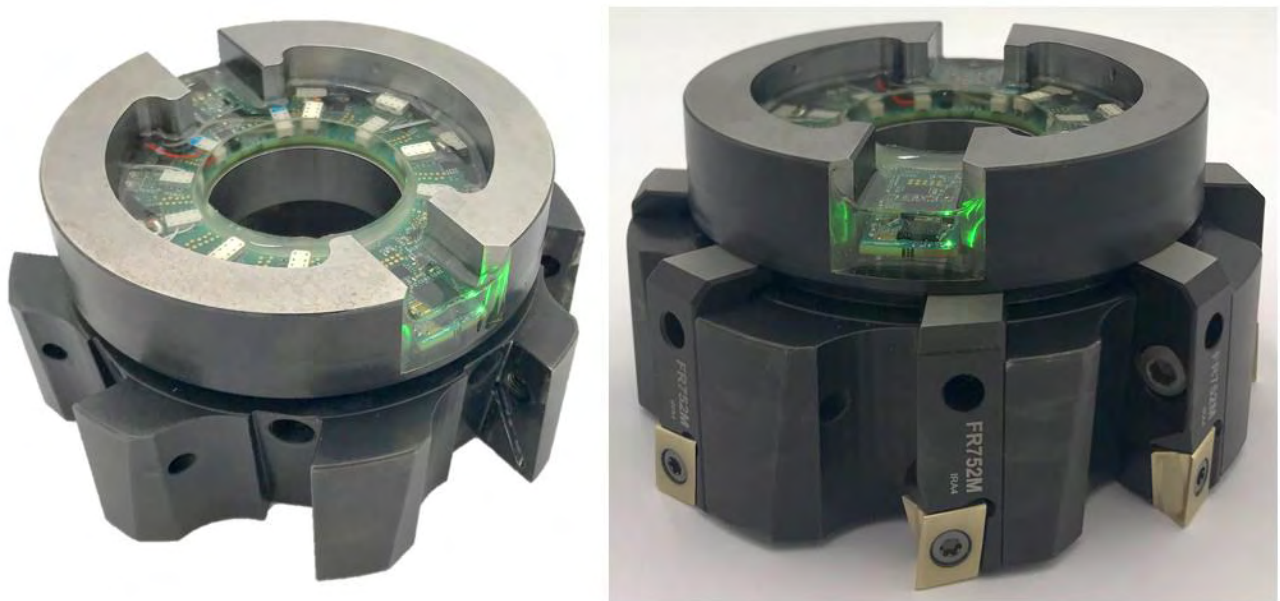


Figure 4.2 The instrumented milling head

Table 4.2 Milling head specifications

Specification	Value
Cutting diameter [mm]	125
Depth of cut maximum [mm]	12
Cutting edge angle (°)	90
Radial rake angle (°)	0
Cutting edge number	8

Insert corner radius [mm]	0.8
Insert material	Tungsten Carbide

Data transmission from the milling head to the Stationary Transceiver Unit (STU) is achieved wirelessly via Bluetooth Low Energy (BLE). The STU is mounted in the machine tool, in a safe distance from the milling head, in order to minimize interference in the BLE signal and data loss. Then, the STU is connected to a serial port of a typical laptop, utilizing a CAN to USB adapter. Data streaming to the laptop is achieved through the CAN-BUS protocol, utilizing a bespoke Python application. This laptop also hosts the tool wear monitoring algorithms. The STU enables bi-directional communication, enabling configuration of the instrumented tool holder through the laptop. The components included in the data transmission chain and their interactions are presented in Figure 4.3

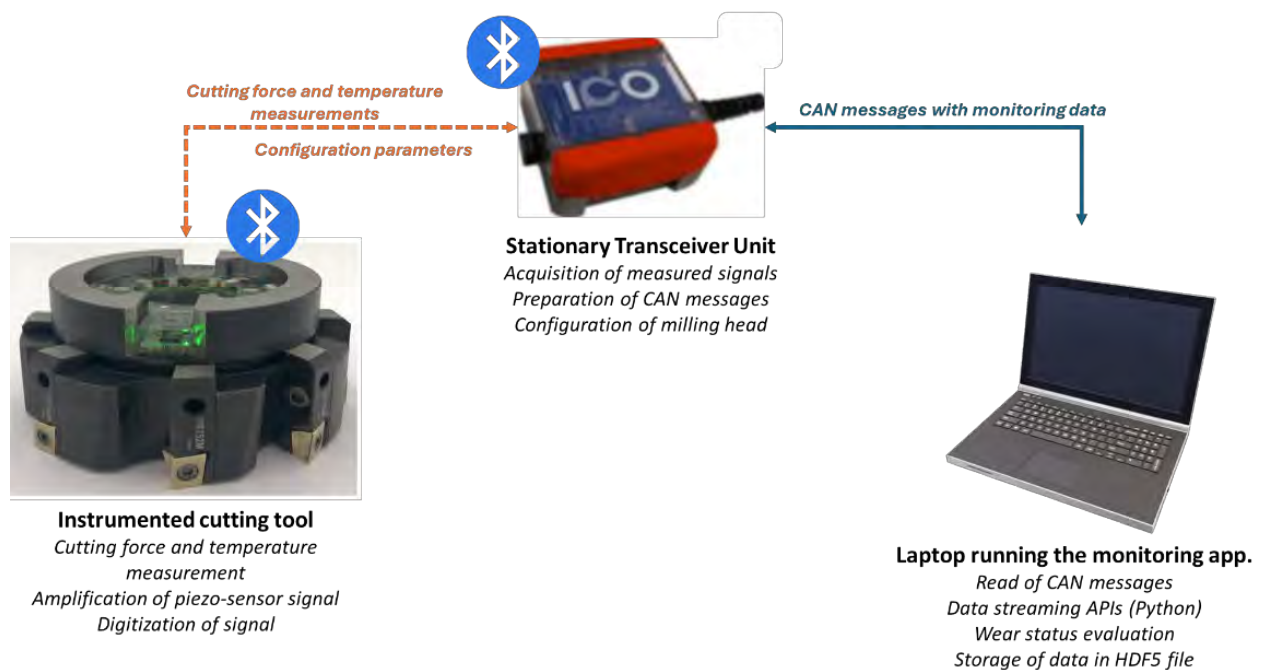


Figure 4.3 The connectivity architecture of the instrumented milling head

4.4. Feature Extraction

The typical first step of signal analysis is pre-processing of the signal. The discrete steps followed during pre-processing of the recorded signals, also form the signal processing pipeline that will be implemented for the actual deployment of the system in real machining scenarios. The first step required is treatment of data loss in the signal. Bluetooth technology has numerous benefits in terms of providing high quality, wireless data transmission, with a low power consumption. However, during transmission of the measured signals from the instrumented milling head towards the STU,

data loss may occur due to a number of reasons. Environmental interference from nearby machinery or other wireless devices, physical barriers, and the limited transmission range of BLE can disrupt communication. Additionally, the milling process generates substantial vibrations and rapid tool movements, potentially causing intermittent signal interruptions. The BLE protocol's limited bandwidth further constrains real-time data transmission, leading to occasional information loss. Although the transmission quality was very good for the largest part of the experimental campaign (less than 0.1% data loss in most of the experiments), some data loss is still inevitable.

To address this, the instrumented milling head implements a counter and a timestamp that are assigned to each measurement and are included in the messages from the instrumented milling head to the STU. This means that the acquired signal is stored in an HDF5 format, which includes a table that provides the timestamp, counter, two force values and one temperature value for each measurement. The counter can then be used to “fill” the gaps in the signal and address information loss. During the pre-processing of the signal the counter is monitored and when one or more missing measurements are observed, they are inserted between the previous and next valid measurements that were transmitted by the instrumented milling head to the STU. Thanks to the high sampling frequency and the low transmission losses, a simple linear interpolation between the valid measurements is sufficient for that step. Figure 4.4 shows the effect of this procedure on the force signal.

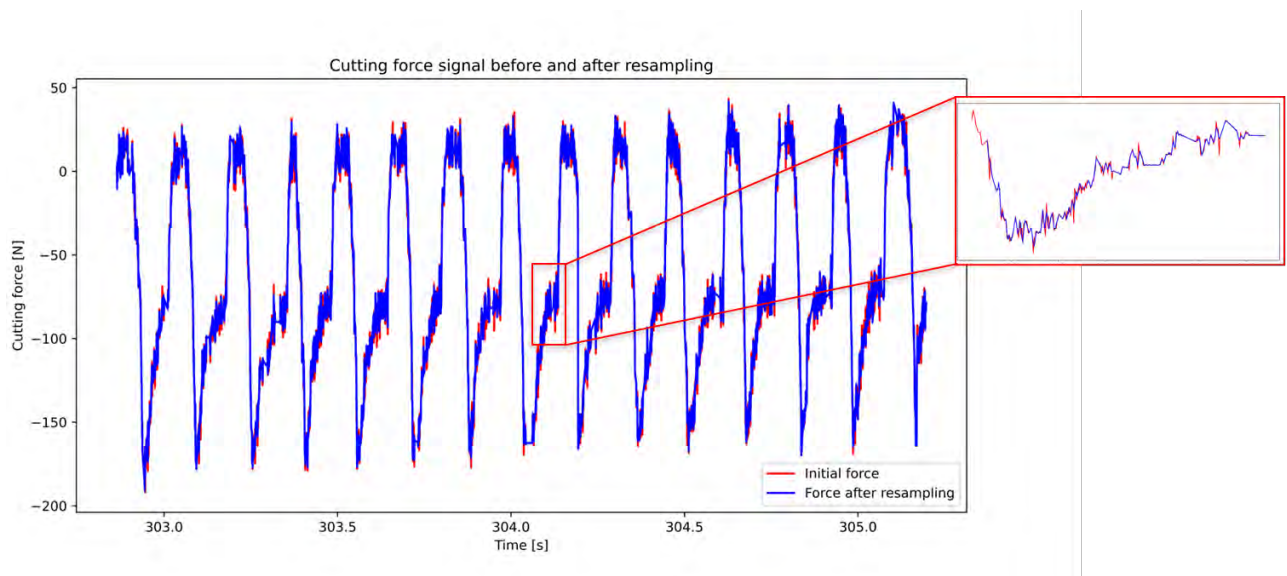


Figure 4.4 Force signal before and after "filling" of missing values

The next step of the analysis is filtering of the cutting force and temperature signals to remove any artefacts caused by the sensors and electronics. For the cutting force signal a high pass filter is applied with a cutoff frequency of 3Hz. Although the force signal exhibited very high quality in general, with a high Signal-to-Noise ratio, as demonstrated by its Fast Fourier Transform (FFT) (Figure 4.5), a high pass filter is applied to ensure that no direct current (DC) offset artefacts are present in

the data due to potential sensor drift or voltage offsets in the electronics. Figure 4.5 presents the FFT of the signal before and after filtering. The peaks highlighted with the red stars are the spindle rotational frequency (7.63Hz for a spindle rotational speed of 458 RPM) and its second harmonic (at 15.26Hz). It is important to note that since the force at each individual insert is measured (as opposed to a cutting force dynamometer where the total force exerted on the tool is measured), the dominant frequency is expected to be the spindle rotational frequency and not the tooth passing frequency.

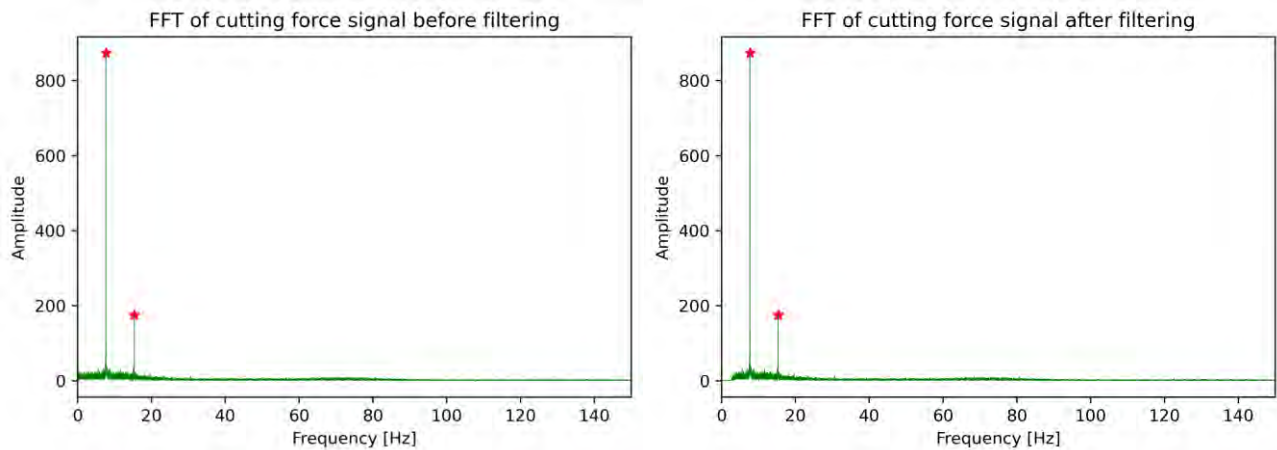


Figure 4.5 FFT of signal before (left) and after (right) filtering

Last step of the pre-processing is smoothing of the temperature signals. During the preliminary analysis of the data a significant ripple was observed in the temperature measurements, so a rolling mean was applied to smooth the temperature signals. The window length for the rolling mean was 1000 samples, which equates to ca. 0.22s of actual time. Figure 4.6 depicts the temperature signal before and after smoothing.

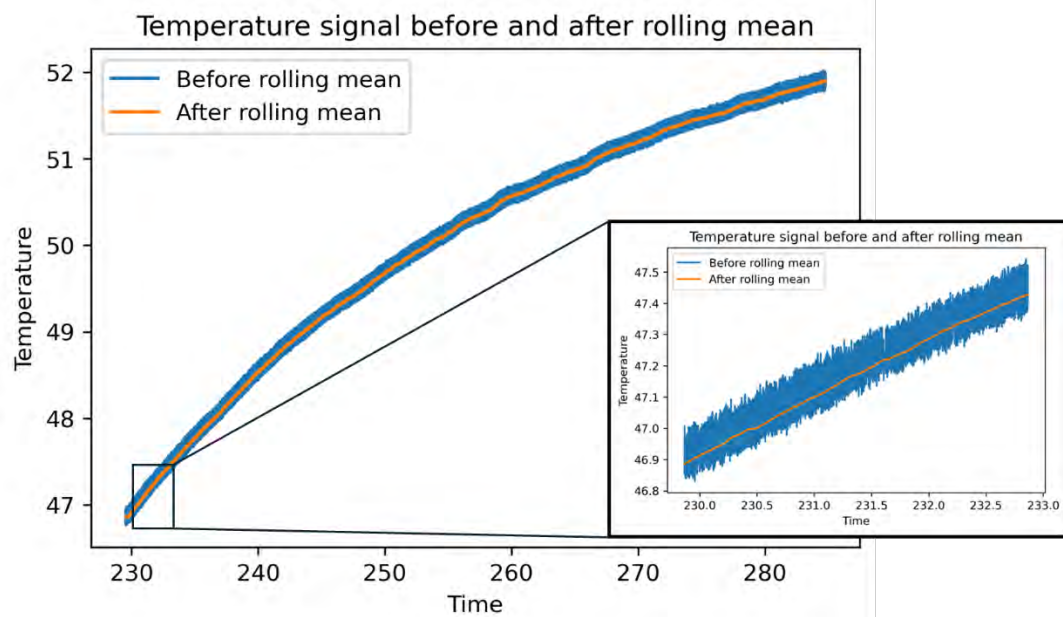


Figure 4.6 Temperature signal before and after smoothing

To conclude the signal processing pipeline, window sampling is performed on the measured signals, using the time (and respectively samples) required for a full rotation of the cutting tool as a window length, since the spindle speed information is available for all the experiments.

The feature extraction process is required to reduce the dimensionality of a signal and decouple the information related to the phenomenon of interest. It is very typical in works related to tool wear monitoring, especially when an Artificial Intelligence algorithm is involved for the wear level prediction, to either extract statistical features from the signal or utilize other dimensionality reduction algorithms (e.g. Principal Component Analysis) [4.29]. A significant advantage of this approach is that multiple features and algorithms (and combinations of those) can be analyzed and tested regarding their correlation with process phenomena and their ability to explain the variance of the measured phenomenon (i.e. tool wear), through pre-defined metrics (e.g. Pearson correlation). This approach simplifies the initial, exploratory phase and might enable the discovery of intricate relationships between signal features that are not evident to the human eye. However, it suffers from two main bottlenecks. Firstly, it is difficult to ensure generalizability and prevent overfitting. The most secure way to control these factors is to use a very large, diverse training dataset. However, this is very costly in terms of resources, in terms of material consumed, cutting tools destroyed and time required conduct the experiments and the extensive tool wear measurements. The second bottleneck is that in the cases where dimensionality reduction algorithms, such as PCA, are employed the extracted features do not have a direct physical relationship with the phenomenon of interest. This means that it is harder to control the explainability of the AI algorithm that will be used for prediction of the tool wear. As a result, this work tries to calculate signal features that have a direct physical relationship with the phenomenon

of interest, reduce the need for a large amount of input data to ensure generalizability, while enabling accurate predictions with a small number of features, thereby minimizing the computational requirements of the approach to support industrial implementation in real-time.

The starting point is the theoretical analysis of the cutting forces and the way tool wear acts upon them. As the tool wear progresses, there are two major changes happening in the shape of the cutting tool. Firstly, the cutting edge becomes round and blunt and, secondly, the contact area between the flank face and the workpiece increases. The former results in a larger work required for chip formation and material removal, while the latter results in larger frictional resistance in the relative motion between the flank face and the workpiece. Both phenomena lead to an increase in the cutting forces that are measured during the milling process [4.30]. Figure 4.7 showcases how the tool-chip interaction is altered as the tool wear progresses and the cutting edge of the tool is becoming blunt.

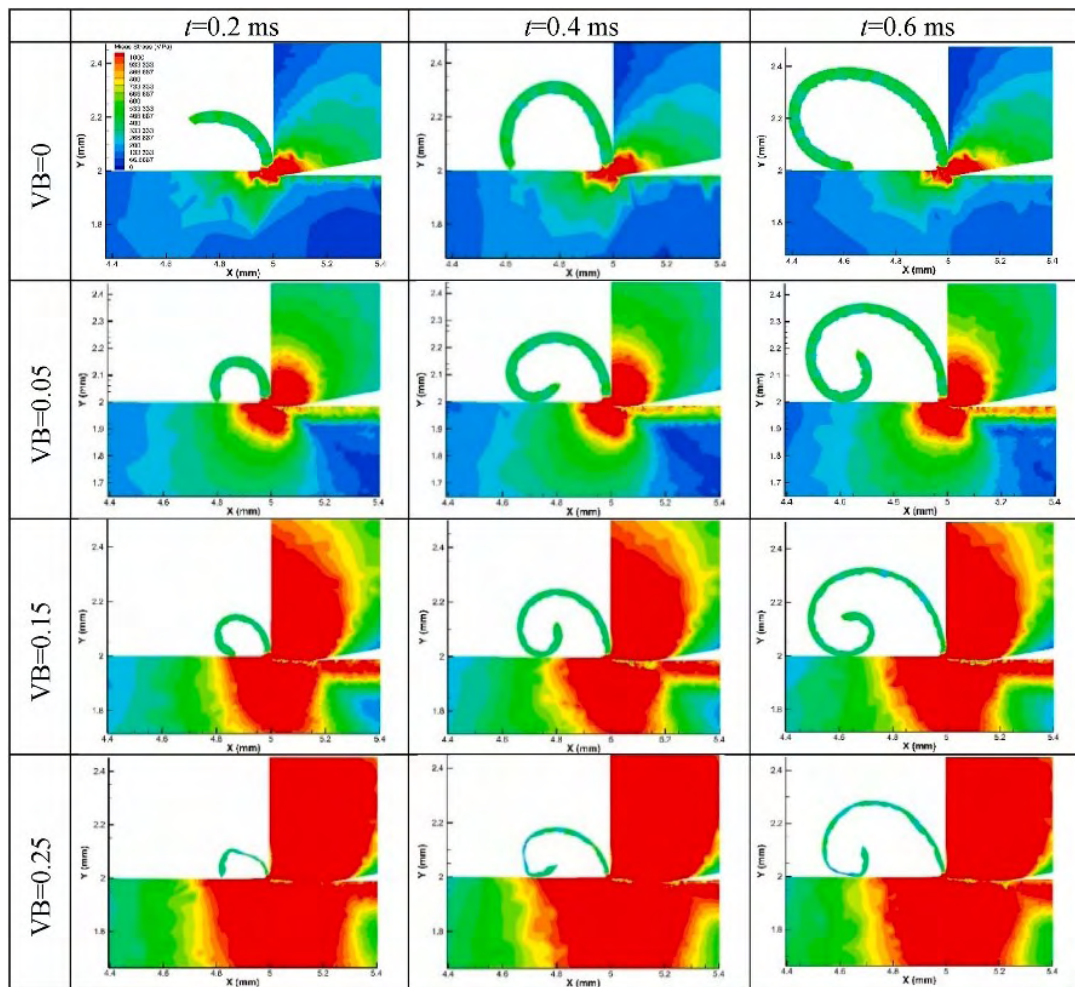


Figure 4.7 Tool-workpiece interaction and chip formation for different flank wear levels [4.30]

In general, when 3-axis milling is considered, cutting forces are analyzed in two different coordinate systems. The first coordinate system is the local, rotating coordinate system of the cutting tool

(LRCS). LRCS rotates with the cutting tool and the three orthogonal directions examined are the tangential, radial and axial. The other CS is the local, non-rotating coordinate system (LNCS) of the workpiece. This might or might not be parallel with the machine tool coordinate system. The three orthogonal directions examined are the X, Y and Z axes (Figure 4.8). The Z-axis is parallel with the axial direction of the cutting tool. The transformation from LRCS to LNCS can be performed using rigid transformation matrices and is trivial. For 5-axis milling, other coordinate systems might be of interest, since the axial direction of the cutting tool is not parallel with the Z-axis, but this is out of the scope of this study. Nevertheless, the methodology followed is similar for 5-axis milling as well. Usually, the analysis is performed in the LNCS, since table dynamometers are used to measure cutting forces, which are stationary. For this study, the analysis is performed in the LRCS, since the piezo sensor that is integrated in the cutting edge seat measures the tangential cutting force.

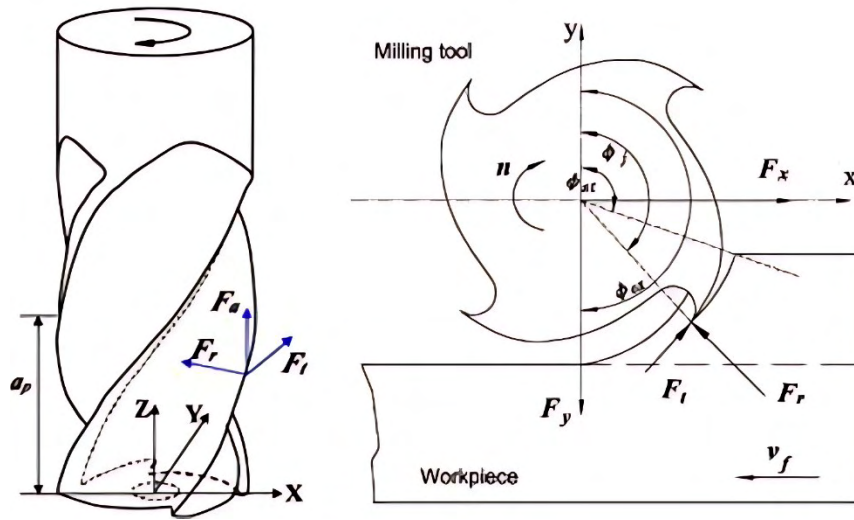


Figure 4.8 Schematic description of cutting force components in milling [4.31]

According to the well-established mechanistic cutting force model of Altintas and Lee [4.32], the three components of the instantaneous, differential cutting force can be calculated as follows:

$$\begin{aligned} dF_{t,j}(\varphi_j, i) &= K_{te}dS(z) + K_{tc}f_z \sin(\varphi_i)dz \\ dF_{r,j}(\varphi_j, i) &= K_{re}dS(z) + K_{rc}f_z \sin(\varphi_i)dz \\ dF_{a,j}(\varphi_j, i) &= K_{ae}dS(z) + K_{ac}f_z \sin(\varphi_i)dz \end{aligned} \quad (4.1)$$

In the equations presented above, $dF_{t,j}$ corresponds to the tangential component, $dF_{r,j}(\varphi_j, i)$ corresponds to the radial component and $dF_{a,j}(\varphi_j, i)$ corresponds to the axial component. The force is discretized along the rotation of the tool and the height of the insert that is immersed in the workpiece. It can be observed that the cutting forces have a linear relationship with the feed per tooth (f_z) and axial depth of cut (z). Finally, (K_c) are the cutting force coefficients and (K_e) the edge force coefficients. For the scope of this paper, only the tangential cutting force component is

of interest, as this is the only one measured by the piezo sensors. By integrating this equation along the axial depth of cut, the total instantaneous cutting force acting on the insert can be calculated.

$$F_{t,i} = \int_0^{a_p} [K_{te}dS(z) + K_{tc}f_z \sin(\varphi_i)]dz = (K_{te} + K_{tc}f_z \sin(\varphi_i))a_p \quad (4.2)$$

The available data are a function of time, so the representation of the equations as a function of time is required. By substituting variables in equations 4.3 and 4.4 with $\varphi = \Omega t$, where φ is the cutting tool rotation angle, Ω is the spindle speed and t is the time, and integrating along the time, over a single spindle rotation period the following is obtained:

$$\int_0^T F_t dt = \frac{K_{te}a_p(\varphi_{ex} - \varphi_{st})}{\Omega} - K_{tc}f_z a_p \left(\cos \frac{\varphi_{ex}}{\Omega} - \cos \frac{\varphi_{st}}{\Omega} \right) \quad (4.3)$$

$$I2 = \frac{a_p(\varphi_{ex} - \varphi_{st})}{\Omega} \quad (4.4)$$

$$I1 = f_z a_p \left(\cos \frac{\varphi_{ex}}{\Omega} - \cos \frac{\varphi_{st}}{\Omega} \right) \quad (4.5)$$

Equation 4.3 is the basis to build an indicator of the wear level of the cutting tool. At any point of any given milling operation, one can integrate the discrete cutting force signal, over one revolution and replace it in equation 4.3. At this point, since all other quantities remain constant (being only dependent to the fixed process parameters), the change on the cutting force due to wear will only be reflected at a change of K_{te} and K_{tc} [4.33]. The contribution of the edge component (K_{te}) is order of magnitudes lower than the cutting component (K_{tc}) [4.34]. This happens because the cutting component is responsible for the chip formation, while the edge component corresponds to the friction between the flank face and the workpiece. Therefore, it is possible to assume with a relatively small error that:

$$\int_0^T F_t dt \approx -K_{tc}I1 \Rightarrow K_{tc} = -\frac{\int_0^T F_t dt}{I1} \quad (4.6)$$

The quantity $\int_0^T F_t dt$ can be calculated from the measured signal and the quantity $I1$ is a function of the selected process parameters. Dividing the two quantities, K_{tc} is calculated and the variation of K_{tc} reflects the wear evolution under specific cutting conditions. Apart from tool wear, cutting temperature has also a non-negligible effect in the cutting force. Depending on the type of material and the level of the cutting temperature in the process, cutting forces can be increased or even reduced for the same set of process parameters. The increase in cutting forces is usually related with increased friction in the tool-chip interface and low conductivity of the material [4.35], while reduction in cutting forces due to elevated temperature can happen, when materials that experience

thermal softening are machined [4.36]. In any case, temperature relates with cutting forces monotonously and its effect needs to be included in the wear level indicator as well, so that the results are not skewed. The simplest way to assume the relationship between temperature and K_{tc} is to consider a linear relationship between the two. Let I_f be the integral of the discrete cutting force signal over one revolution (Figure 4.9), which is performed using Simpson's composite 1/3 rule, and $\bar{T}$ be the average cutting temperature over one revolution, the wear indicator can be calculated as follows.

$$Index = \frac{I_f}{\bar{T} * K} \quad (4.7)$$



Figure 4.9 Integration of force signal over one revolution

It is important to note here that this wear level indicator arbitrarily assumes this specific relationship between the different quantities. However, the scope of the study is not to conclude in identifying an indicator that can be used for tool wear level estimation as is, but to explore the relationship of these specific quantities with wear level, as potential candidates for input features to the AI-based predictive models. The procedure of building that indicator and testing its general correlation with the phenomenon of interest, which is tool wear progression, helps in shedding light on the way that the physics of the process and the established machining theory, can help in identifying robust features that can be used to train data-driven models. Figure 4.10 showcases the logic and steps taken during the feature engineering process, in order to conclude to the input features that will be used to train the AI algorithm.

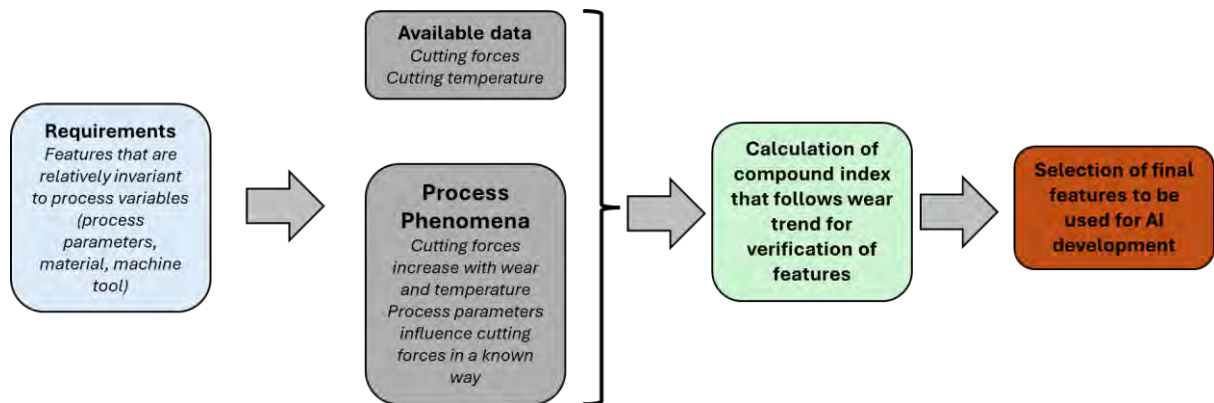


Figure 4.10 Steps of the feature engineering process

In experiments with constant process parameters, the compound wear index exhibits an almost linear relationship with tool wear, allowing for straightforward prediction, as shown in Figure 4.11. However, when varying process parameters are introduced, the wear index becomes ineffective due to the non-linear behavior arising from variations in cutting force coefficients that are dependent on these parameters (i.e. cutting speed, axial and radial depth of cut) [4.34], as illustrated in Figure 4.12. This highlights also the benefit of utilizing AI for such applications. Upon confirming a relationship between the input features and the phenomenon of interest, that follows a monotonous trend to a degree, then AI can effectively map the relationship between the input features and the phenomenon, saving a lot of development time and ensuring accuracy. Utilizing input features that are driven by the physical mechanisms of the process, the explainability and transparency of the AI models is retained, which helps with transferability between different processes and systems, as well as maintenance after deployment.

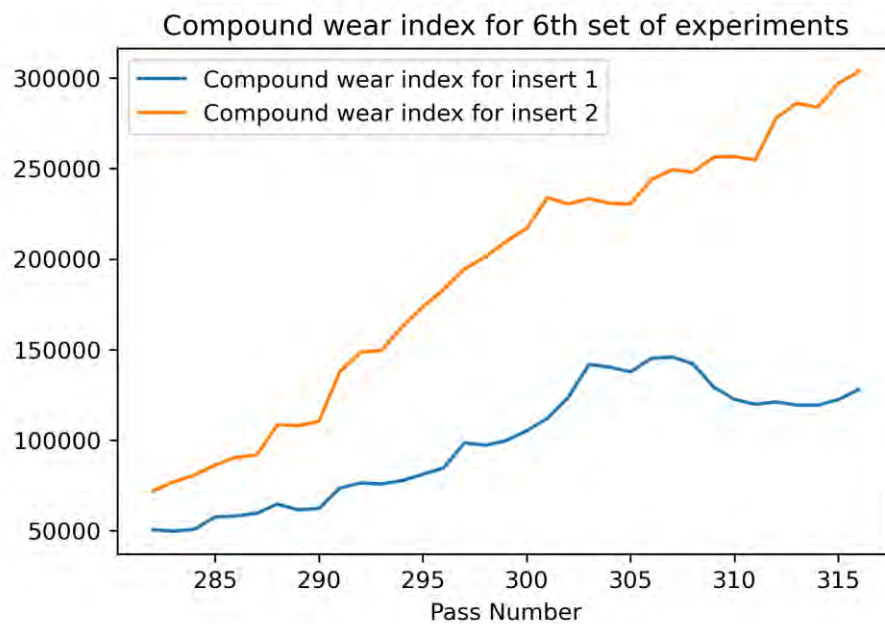


Figure 4.11 Compound wear index for fixed process parameters

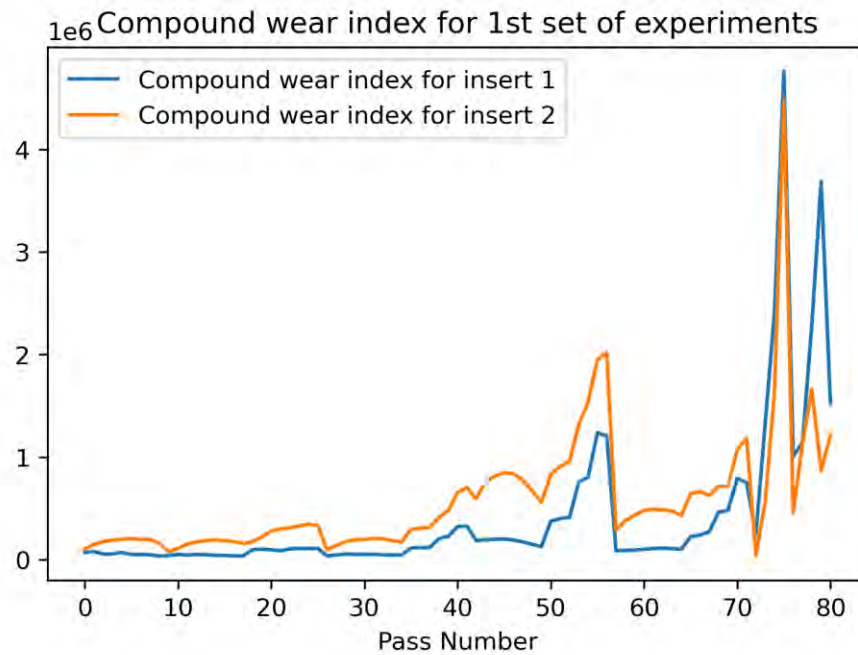


Figure 4.12 Compound wear index for varying process parameters

4.5. Machine Learning Approach

4.5.1. Experimental Setup

The machine tool that was utilized for the experiments that took place to generate the dataset for the development of the tool wear monitoring algorithms was a Mazak MTV-815/80 vertical machining center, equipped with a Mazak Mazatrol MTV 640M controller. The material that was processed was 1.2085 high-alloy, pre-toughened tool steel. The cutting inserts that were equipped on the milling head were Walter LNHU130608R-L55T WSP45G tangential rhombic. Figure 4.13 shows the experimental setup. On the right-hand side, the established Bluetooth connection is indicated by the green light on the instrumented milling head.



Figure 4.13 The instrumented milling head installed on the Mazak machine tool

A diverse set of machining experiments was conducted for training of the tool wear level estimation algorithms. A total of 40 different experiments took place, under dry and flood cooling machining conditions. Both climb and conventional cutting was performed. Table 4.3 presents the process parameter ranges. The experiments were conducted in 6 groups, with each group utilizing a new set of brand-new inserts. Groups TR1, TR2 and TR3 aimed to create a diverse dataset by varying the process parameters. The experiments were performed with constant cutting speed, while progressively increasing the axial depth of cut. For each level of the axial depth of cut (DoC), three different levels of feed per tooth and two levels of radial depth of cut were examined. The process parameters were altered one at a time for each experiment. For Group TR4, the process parameters were kept constant and a new set of inserts was used until their end of life. The goal was to establish a wear trendline over time. Group TR5 was designed to also assess the effect of cutting speed on the cutting temperature. As such, all process parameters were kept constant, except for the cutting speed, which was varied. This could provide an insight on the rate of increase of cutting temperature for different cutting speed values. Group TR6 was conducted with constant process parameters and flood cooling (contrary to the rest of the five groups that were conducted with dry machining), which means that cutting temperature was also relatively constant during this last group. The process was stopped regularly to measure the wear level of the inserts. A YF-2010 video measuring system was used to measure the flank wear at the cutting edge of the inserts. During the experiments, the cutting force at two inserts and the cutting temperature at one insert were recorded at a sampling rate of 4500Hz. These three signals were later used for the analysis and development of the tool wear estimation algorithms. The process parameters were selected according to the recommendations of the cutting tool manufacturer, which are accessible in the forms of online libraries for customers. By importing the cutting tool (milling head and insert data), machining process type and workpiece material, a range for each of the process parameters is recommended, so that the insert performs best. It was decided to follow these recommended parameters, since this is what would happen in an actual industrial setting, making the dataset as realistic as possible. The total number of

experiments was selected in an effort to develop a machine learning model that could be trained using a relatively small number of experiments. The key bottleneck for industrial implementation of machine learning approaches is the need for extensive datasets. In this specific case, the generation of the dataset for training the models, required only a single shift of the machine tool and machine tool operator, which can be considered acceptable, given the benefits it provides.

Table 4.3 Table of experiments for the generation of the training dataset

Group	Process parameter ranges				
	Cutting speed [m/min]	Feed per tooth [mm]	Axial DoC	Radial DoC	Type of cooling
TR1	150	0.05 – 0.15	0.5 – 2.5	32 - 120	Dry Machining
TR2	150	0.13 – 0.2	2 – 4.5	120	Dry Machining
TR3	180	0.13	5 – 5.5	120	Dry Machining
TR4	180	0.13	6	100	Dry Machining
TR5	130 - 180	0.13	2.5	90	Dry Machining
TR6	120	0.13	4	90	Flood Cooling

4.5.2. Wear Behaviour of the Cutting Tools

In this section, a brief description of the behavior of the cutting tools and the wear modes observed is presented. In general, the wear behavior of the inserts adhered to what is expected in a typical machining scenario. The main wear mode exhibited in the cutting inserts was flank wear, which showed a normal behavior. A faster wear rate during the first meters of machining length, followed by steady-state and slow wear during most of the service life of the insert (Figure 4.14). At the end of the service life of the inserts, accelerated wear was observed until the rupture of the cutting edge (Figure 4.15). The wear behavior, in terms of trend and not actual wear level, was similar regardless of the material removal rate. However, a significant difference was observed between experiments where coolant was used and the dry machining experiments. The service life during dry machining was 10 meters on average, while for machining with coolant it was 4.5 meters. The key reason attributed to the reduced tool life during machining with coolant was the thermal shock that was

introduced on the inserts, which influenced the stability of the coating. Such a performance was expected, since the recommendation of the manufacturer for these inserts is to be used without coolant. However, a run of experiments with cooling was applied to also test the behavior of the sensor-integrated milling head and its electronics under a flood cooling scenario. Machining with flood cooling showed no difference compared to the dry machining, in terms of the behavior of the equipment. This was validated using the data loss metric of the system, which was not affected. Additionally, no abnormalities were observed in the measured data. A slight chipping of the cutting edge was observed when high axial depth of cut values (more than 5mm) were utilized. Chipping of the cutting edge was also much more prominent when coolant was used (Figure 4.16).

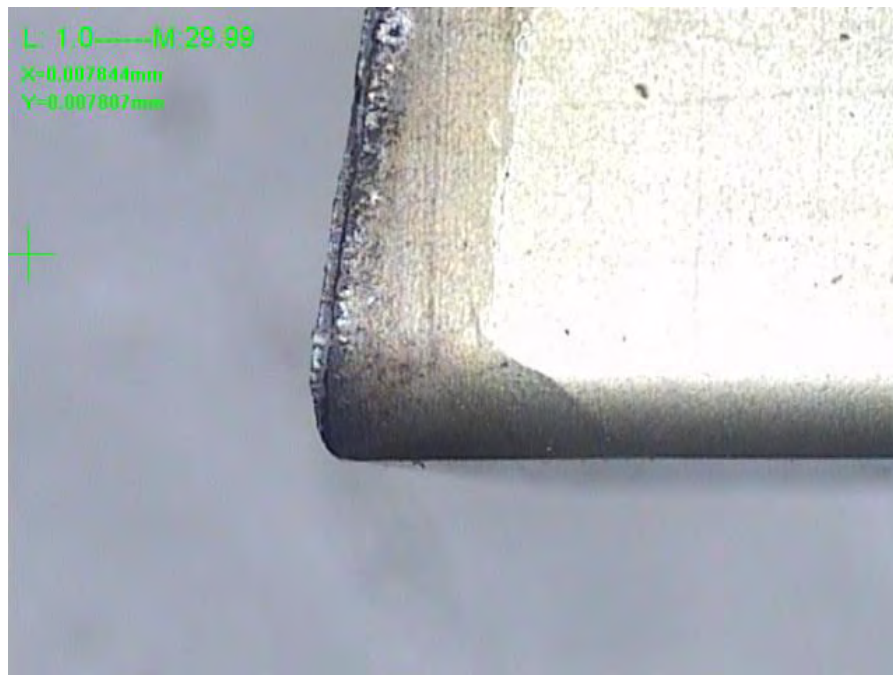


Figure 4.14 Flank wear of an insert during the steady state wear phase

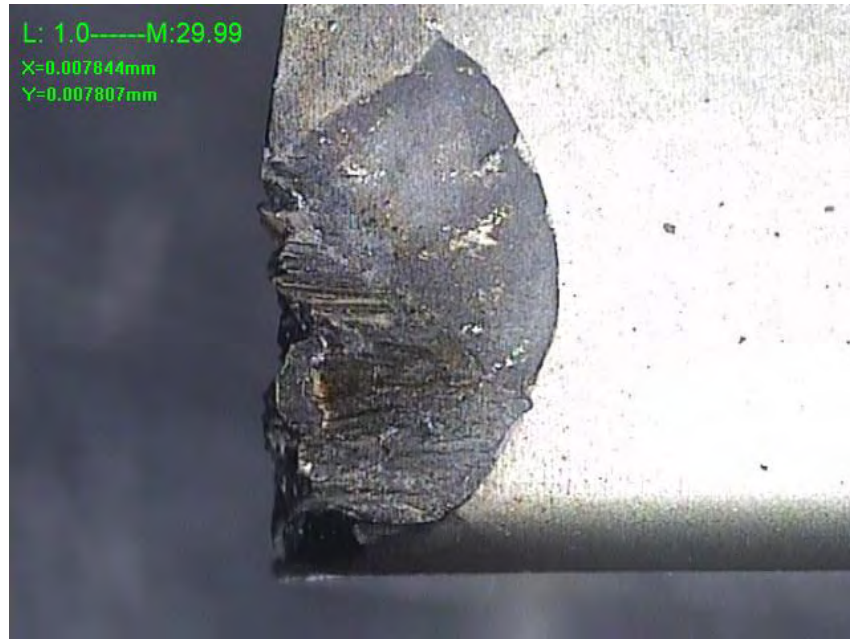


Figure 4.15 Ruptured cutting edge due to excessive wear

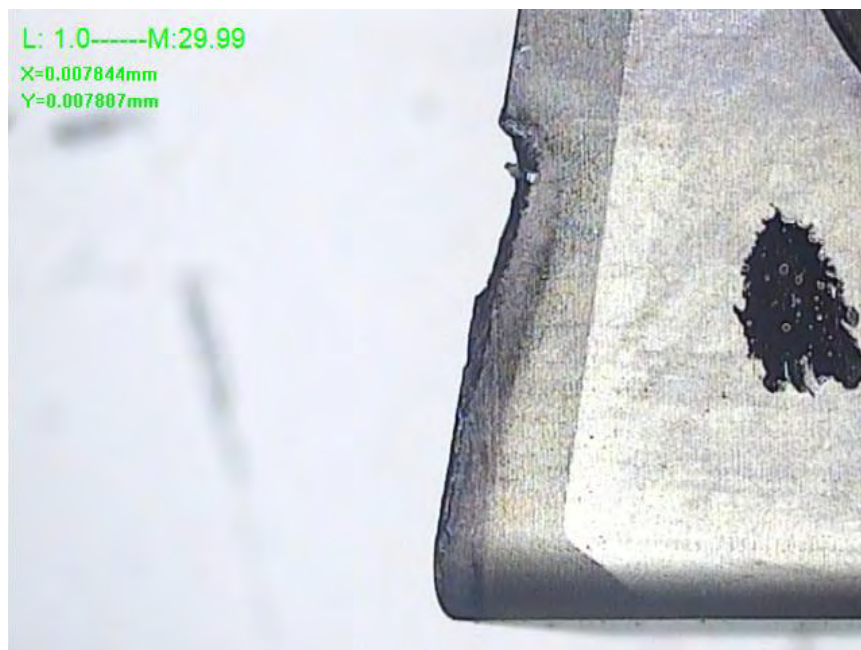


Figure 4.16 Chipping on the cutting edge of an insert that was used with flood cooling

4.5.3. Selection of AI Models

The selection of the AI models is based on several criteria that are linked with the targeted application. Firstly, a supervised learning algorithm suits the proposed approach, so that it is based on the ground truth wear measurements. Next, the algorithms should be capable of capturing non-linear relationships between the input features and phenomenon of interest, which as has been

explained in the previous section, is the case for tool wear prediction. Additionally, the selected models should be computationally efficient to support deployment in real-time applications. Another critical consideration is that the algorithms should be able to handle data of different orders of magnitude without the need for normalization or scaling. The input features that have been selected are in vastly different orders of magnitude (from 10^{-2} to 10^3), which would hinder the performance of algorithms, such as Support Vector Machines, without normalization or scaling [4.37]. By examining the works included in the literature review, some type of data normalization or dimensionality reduction through, which inherently applies normalization to an extent, has been applied, when algorithms, such as SVM were utilized. However, these processes introduce additional complexity in the data pre-processing pipeline and, most importantly, they limit the transferability of the model to a completely new application, where the input feature ranges might vary. Apart from these, the criteria defined in Chapter 3 are still relevant for this application as well. Table 4.4 presents the decision matrix table for the comparison of the most popular AI models for classification and regression.

Table 4.4 Decision matrix table for selection of the tool wear prediction models

Criterion	Weight	SVM	ANN	CNN	RF	KNN	DT	LR
Real-time suitability	0.15	5	3	2	4	1	5	5
Computational efficiency	0.10	5	2	2	3	2	5	5
Explainability	0.10	5	2	2	3	2	5	5
Robustness to noise	0.10	4	3	4	5	2	3	3
Training data requirements	0.10	4	2	3	3	2	3	3
Generalization across conditions	0.15	4	4	4	3	2	2	3
Handling different input magnitudes	0.30	2	3	5	5	1	5	2
Total score		3.80	2.85	3.50	3.95	1.60	4.15	3.40

Based on the results of the table, a Decision Tree classifier and a Random Forest regressor have been selected, since they fulfil all the criteria set for algorithm selection. The Decision Tree algorithm is a supervised learning model that partitions data into subsets based on feature values, creating a tree-like structure comprising nodes, branches, and leaves, as illustrated in Figure 4.17. In this structure, internal nodes represent decisions based on specific features, branches indicate potential outcomes,

and leaf nodes correspond to final predictions or class labels. The tree is constructed through recursive data splitting at each node, with the objective of maximizing information gain or minimizing impurity, which can be measured using metrics such as Gini impurity or entropy.

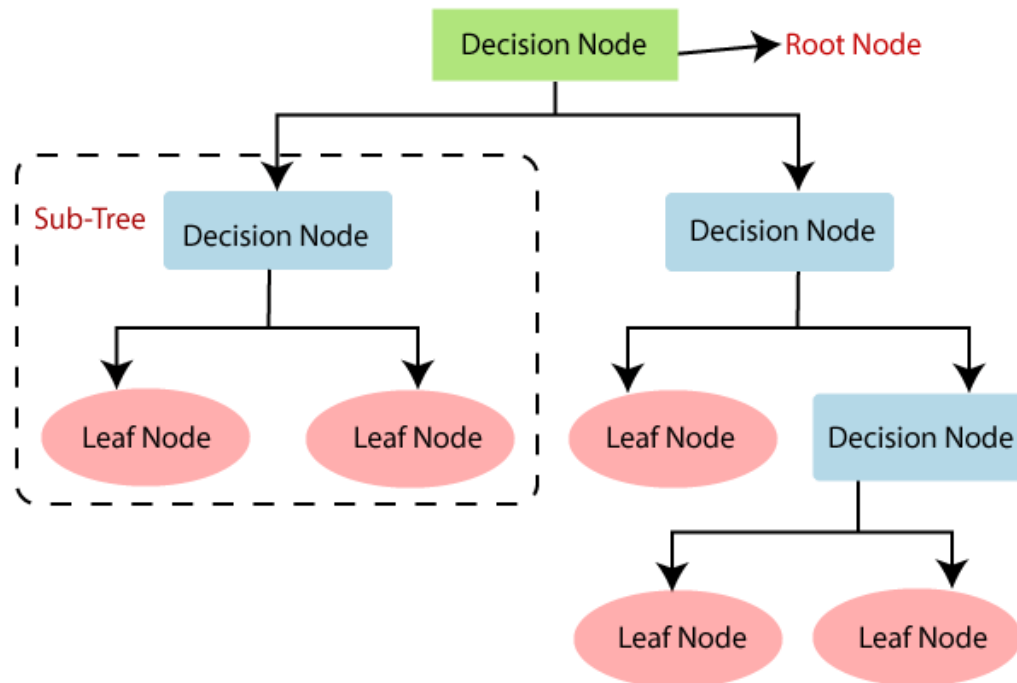


Figure 4.17 Working principle of the Decision Tree algorithm [4.38]

The Random Forest algorithm builds upon the foundation established by Decision Trees, employing an ensemble of multiple decision trees to enhance predictive performance. Each tree is trained on a random subset of the data, utilizing a technique known as bootstrapping. Additionally, at each split within the tree, a random subset of features is considered for the decision-making process. This approach helps to combat overfitting, a common issue with individual decision trees, as illustrated in Figure 4.18. By diversifying the training sets and features, Random Forest reduces the likelihood of creating overly complex models that do not generalize well to unseen data. Upon completion of the training phase, each tree within the Random Forest generates its own prediction for a given input. The final output of the Random Forest model is determined by aggregating the predictions from all individual trees, typically by averaging the values for regression tasks or taking a majority vote for classification tasks. This ensemble method not only enhances the stability of the model but also significantly reduces variance, making Random Forest an effective tool for handling non-linear relationships inherent in the data. Its ability to generalize well to different datasets and its robustness against noise and outliers make it particularly suitable for predicting tool wear, allowing for more accurate assessments and timely interventions in machining processes. Furthermore, the interpretability of Random Forest models can be enhanced through techniques such as feature importance analysis, providing valuable insights into which features most significantly influence wear predictions, thereby supporting better decision-making in manufacturing operations.

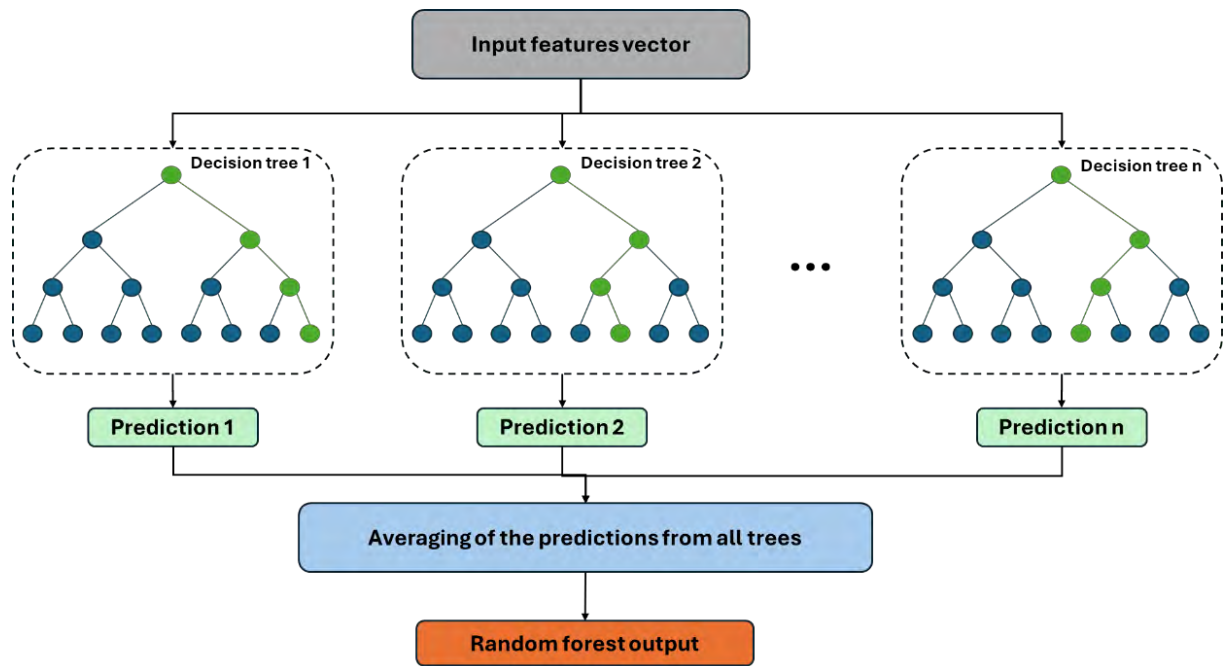


Figure 4.18 Working principle of the Random Forest algorithm

For both cases, the data were split at an 80%-20% for training and testing respectively. For the regression, the actual flank wear values that were measured during the experiments were used to train the algorithm. For the classification, three distinct wear levels were introduced, namely “break-in”, “steady-state” and “accelerated” wear level. These three levels conform to the typical wear behavior of a milling cutting tool, which is shown in Figure 4.19. In general, cutting tools in machining experience a rapid increase in the wear level, as soon as they start being used, called the break-in period. Next, for the most part of the tool life, the wear progresses with a steady-state, almost linear fashion. Finally, the tool reaches the point of accelerated wear, where the wear rate increases again. Especially in coated cutting tools, this can be linked with a (partial or full) delamination of the coating, which provides wear stability. The accelerated wear phase also does not last long, with the tool reaching its end of life either due to breakage or due to excessive wear level that degrades its cutting performance. It is usually recommended to replace the cutting tool once the last phase is reached to avoid phenomena, such as abrupt breakage, which might damage the machine tool components or scrap the machined part.

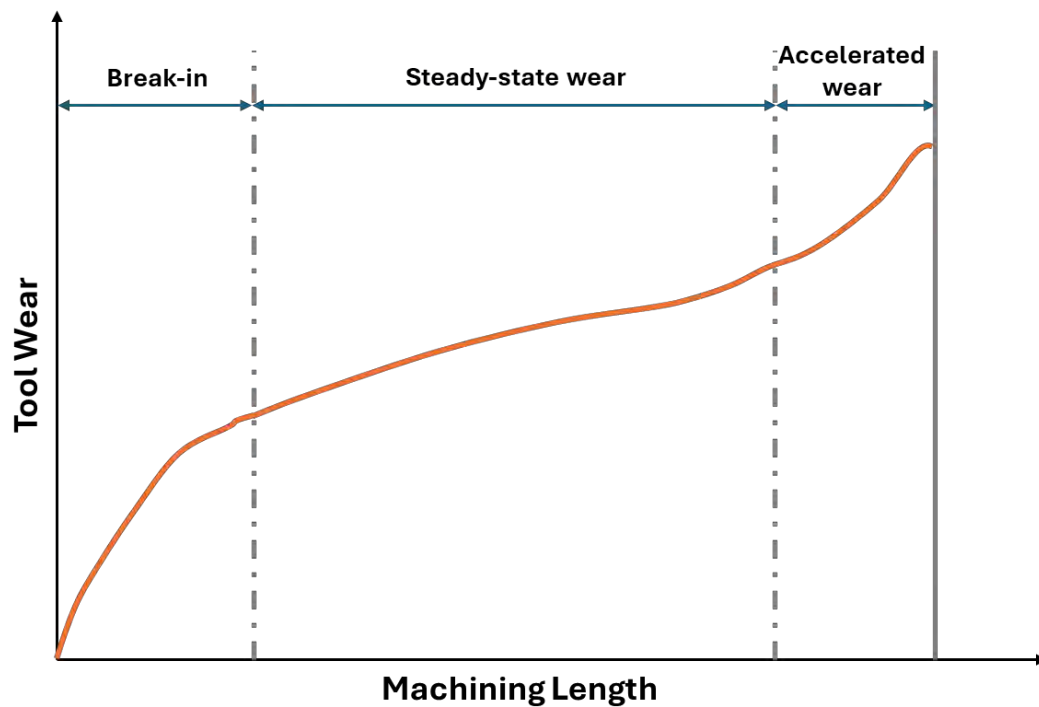


Figure 4.19 Typical wear progression of a milling cutting tool

To improve the predictive capabilities of both models, hyperparameter tuning was employed. For both models, randomized search has been performed, due to its abilities to efficiently explore the parameter optimization space. For the Decision Tree classifier, the “one versus rest” score of the area under the Receiver Operating Characteristic (ROC) curve was used as an optimization metric, while for the Random Forest regressor, the R^2 was used as an optimization metric. The algorithms, as well as hyperparameter tuning have been implemented in Python, utilizing scikit-learn [4.39], which is one of the most popular Python packages for AI modelling and deployment. Based on the optimization results, the following hyperparameters were utilized for each of the algorithms, which are presented in Table 4.5 and Table 4.6.

Table 4.5 Best hyperparameters for the Decision Tree classifier

Hyperparameter description	Values
Maximum depth: Control the maximum depth to which a decision tree is allowed to grow	30
Min_samples_split: Defines the minimum number of samples required for a node to be considered a split node. It is used as a threshold to control when split nodes can be formed	5

Min_samples_leaf: Defines the minimum number of samples required for a node to be considered as a leaf node. It is used as a threshold to control when leaf nodes can be formed	5
Max_features: It controls the number of features that can be considered when looking for the best split in the decision tree	$\log_2$

Table 4.6 Best hyperparameters for the Random Forest regressor

Hyperparameter description	Values
Maximum depth: Control the maximum depth to which a decision tree is allowed to grow	30
Min_samples_split: Defines the minimum number of samples required for a node to be considered a split node. It is used as a threshold to control when split nodes can be formed	5
Min_samples_leaf: Defines the minimum number of samples required for a node to be considered as a leaf node. It is used as a threshold to control when leaf nodes can be formed	5
Max_features: It controls the number of features that can be considered when looking for the best split in the decision tree	$\log_2$
Number of estimators: The number of decision trees that the random forest builds to make the prediction	100

4.6. Performance Evaluation and Generalisation

4.6.1. Decision Tree Classifier

The Decision Tree plot provides a visual representation of the decision-making process of the model, as depicted in Figure 4.20. By investigating this plot, one can get valuable insights regarding the decision-making process of the classifier. At each node, a condition regarding the value of one of the features is applied. If the condition is true, the tree branches to the left of the node and if it is false, it branches to the right of the node. The nodes, where the branch further splits are the split nodes, while the nodes, where the branch ends, are the leaf nodes. At the leaf node, there are two quantities of interest that can be examined. The “gini”, which refers to the gini impurity. The gini is the probability of two samples, which are randomly picked in a node of the decision tree, to belong in the same class. The gini impurity can be calculated by subtracting gini from the value of one. Then,

it is clear that the goal of the decision tree is to minimize the gini impurity at the leaf nodes. The other interesting quantity is the “value” vector. This vector shows the percentages of the classes, to which the samples of the node belong. The first index of the vector corresponds to the “Break-in” class, the second to the “Steady-State” class and the third to the “Accelerated” class. Apart from looking at the exact values, one can visually estimate the impurity of each node and the class that retains majority in each node. Orange coloured nodes correspond to the “Break-in” class, green coloured nodes to the “Steady-State” class and purple coloured nodes to the “Accelerated” class. The accent of the colour depicts the impurity, where the stronger the accent, the less the impurity of the node.

Apart from the analysis of the decision tree plot, numerical metrics can be provided to show the classification performance of the decision tree. The classification report (Table 4.7) provides some key metrics that are commonly utilized to assess the performance of the classifier. Precision measures the proportion of correct positive predictions out of all predicted positives, indicating how many of the predicted instances for a class were actually correct. Recall, on the other hand, measures the ability of the model to correctly identify all relevant instances of a class, indicating how many actual instances of a class were correctly predicted. F1-score is the harmonic mean of precision and recall, offering a balanced evaluation of the model’s performance by considering both false positives and false negatives. The confusion matrix (Figure 4.21) provides a detailed breakdown of correct and incorrect classifications across the three classes. It can be observed that the model correctly classified all samples in the testing set, with only a single misclassification in the break-in class. Finally, the multiclass ROC curve illustrates the performance of the classification model in distinguishing between multiple classes using the one-vs-rest approach, as illustrated in Figure 4.22. Each class is evaluated individually against the others, with the areas under the curve (AUC) representing the model’s ability to correctly classify each class. In this analysis, Accelerated class achieved a perfect AUC score of 1.00, while break-in and steady-state showed excellent performance with AUC scores of 0.99. The dashed black line in the plot represents the random classifier, serving as a baseline for comparison. The high AUC scores for all classes indicate strong predictive accuracy of the model across all categories.

Table 4.7 Classification report of the Decision Tree classifier

Class	Precision	Recall	F1-score
Break-In	0.96	1.00	0.98
Steady-State	1.00	0.97	0.99
Accelerated	1.00	1.00	1.00

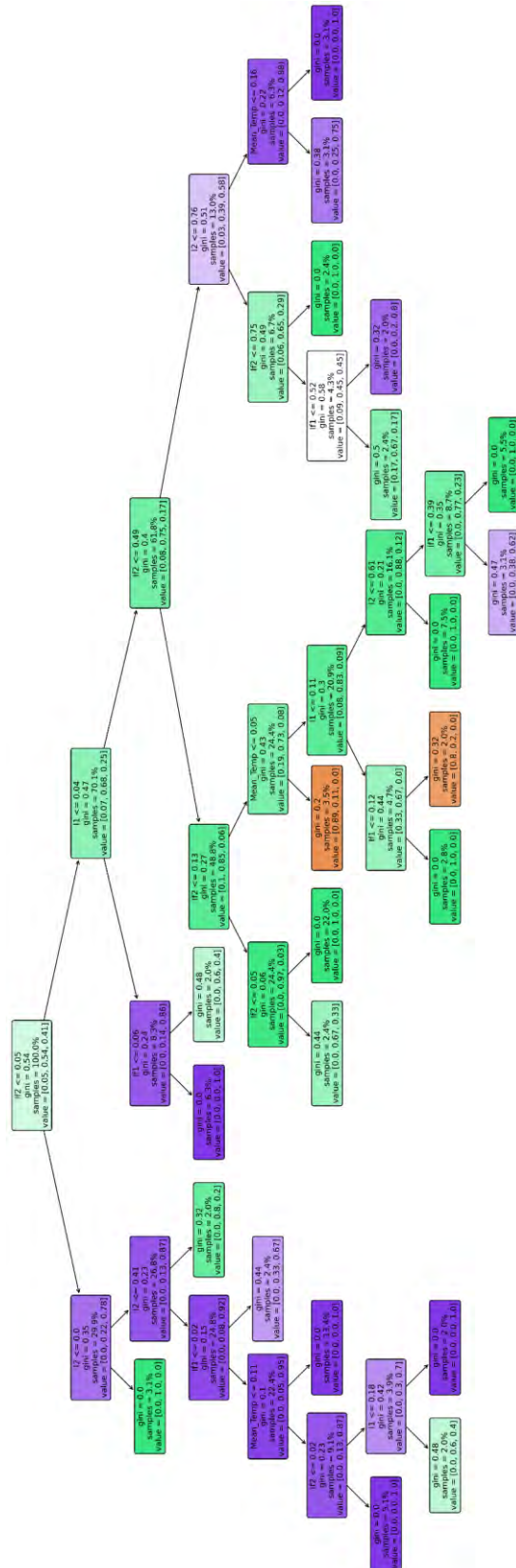


Figure 4.20 Decision Tree plot

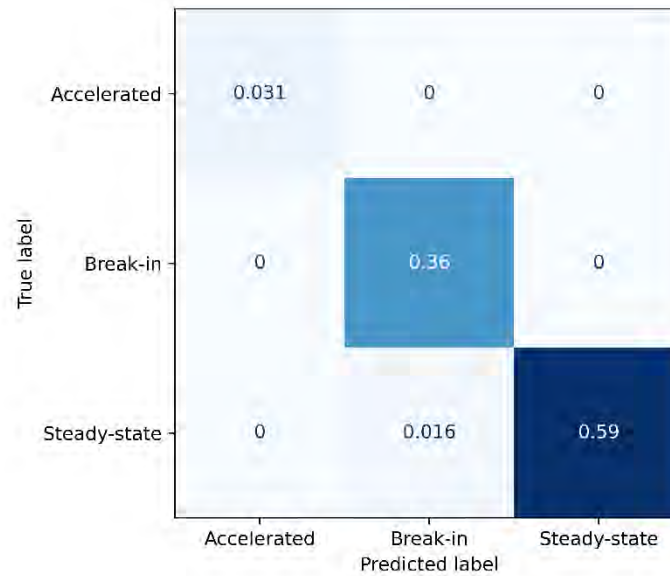


Figure 4.21 Confusion matrix of the Decision Tree classifier

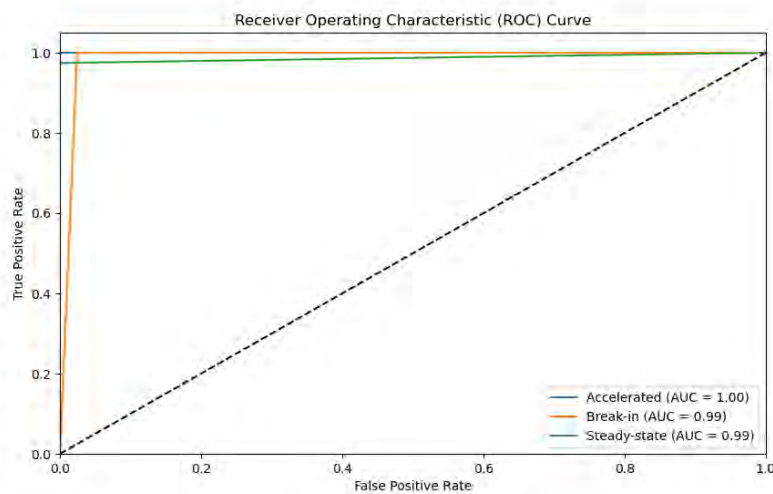


Figure 4.22 Multi-class ROC curve of the Decision Tree classifier

It is also important to understand the role of the different features in the prediction of the wear level. Figure 4.23 depicts the permutation importance for each feature. The permutation importance evaluates the importance of a feature, by measuring the magnitude of deterioration (accuracy loss) of the model, when the values of the feature are randomly shuffled. According to Figure 4.23, the integral I1 (see Equations 4.3 – 4.5) and the force integral of insert 2 dominate, with the force integral of insert 1 following. The mean temperature and integral I2 (see Equations 4.3 – 4.5) have a less significant effect. The difference between the integrals I1 and I2 is anticipated, as I1 is related to the cutting component in the mechanistic cutting force model, whereas I2 is related to the edge

component. The cutting component is usually order of magnitudes higher than the edge component [4.32]. It is also interesting to note that the integral I1 plays a decisive role in the prediction. This highlights the assumption that utilizing features based on the machining theory and physics is vital for the development of a robust model.

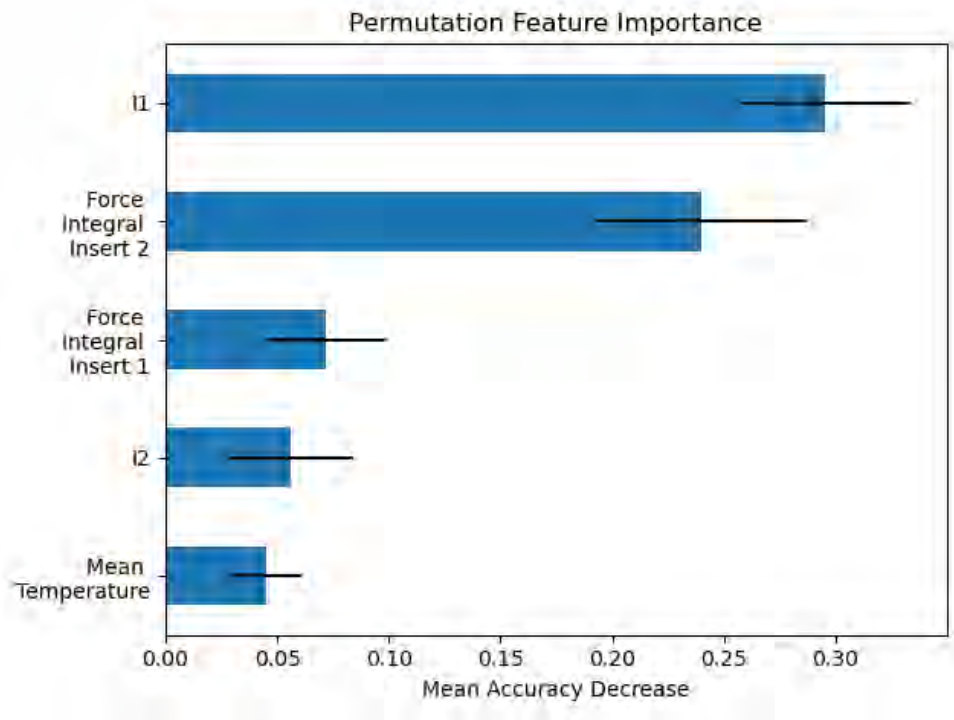


Figure 4.23 Permutation feature importance for the Decision Tree classifier

4.6.2. Random Forest Regressor

To verify the wear estimation performance of the Random Forest regressor, a set of typical evaluation metrics, based on the prediction error are utilized, namely the Mean Squared Error (MSE), the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE). The first two, tend to calculate a larger “penalty” for larger errors compared to the smaller ones, as the error value is squared, while MAE has a linear relationship with the error magnitude. It is also interesting to note how the tuning process affected the R^2 value, providing an improvement of 8.64%. The evaluation metrics are presented in detail in Table 4.8. They can also be visualized in Figure 4.24, which presents the predicted wear values from the random forest compared to the measured ones, within the testing dataset. The red line corresponds to the $y = x$ curve and indicates the predictions of a perfect regressor.

Table 4.8 Evaluation of prediction performance of Random Forest regressor

Evaluation metric	Performance of regressor
R^2 before tuning	0.8848
R^2 after tuning	0.9613
Mean Squared Error (MSE)	0.0005
Root Mean Squared Error (RMSE)	0.0230
Mean Absolute Error (MAE)	0.0132

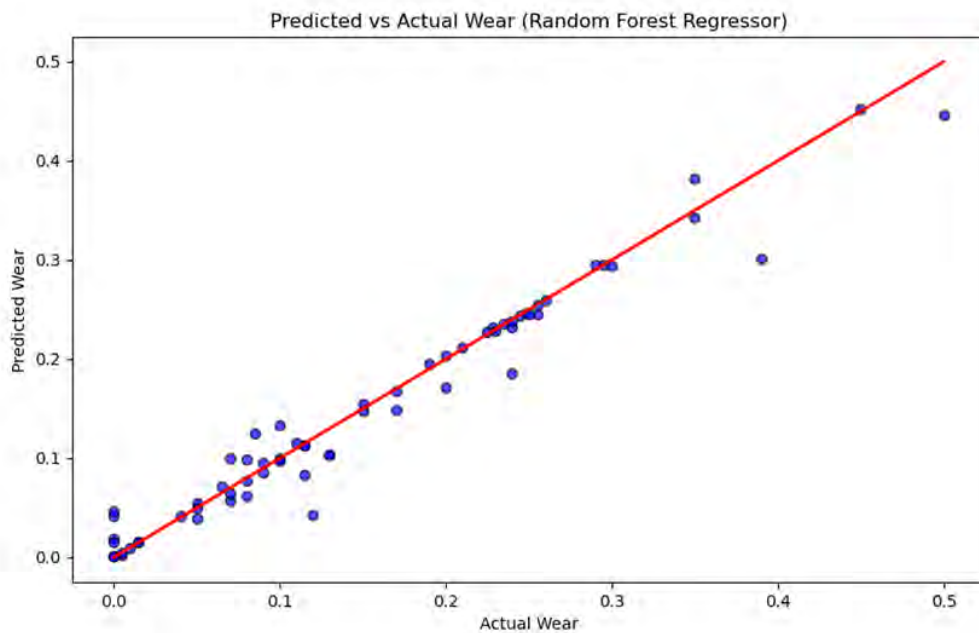


Figure 4.24 Comparison between predicted and actual wear values

Similar to the Decision Tree case, the permutation importance of the input features is calculated for the Random Forest regressor as well. The results are presented in Figure 4.25. A similar behaviour with the Decision Tree can be observed, albeit with a finer balance between the feature importances. This could be attributed to the fact that the Random Forest uses an ensemble of trees.

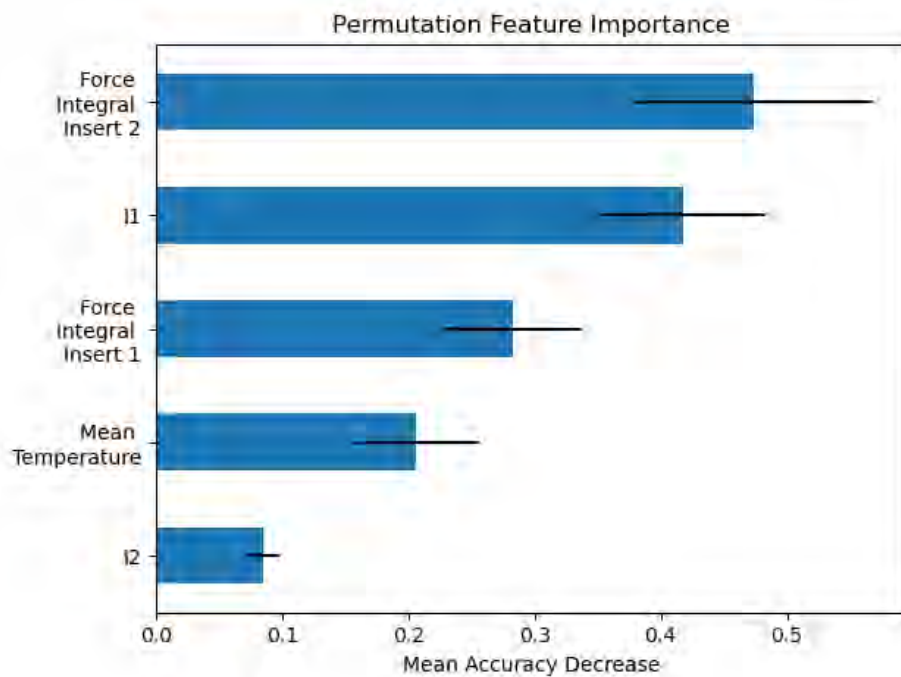


Figure 4.25 Permutation feature importance for the Random Forest regressor

4.6.3. Generalizability Investigation in New Datasets

The last part of this work is to investigate how well this approach can generalize into new, unknown datasets. For that purpose, a data from the instrumented milling head, along with wear measurements were retrieved, during machining trials that were conducted in the facilities of TU Wien. To verify the generalizability of the approach, two different cutting inserts, two workpiece materials and a diverse set of process parameters were tested. The instrumented milling head was installed in a different machine tool, which was a Mori Seiki NHX 6300 horizontal machining centre, with a Mitsubishi controller (Figure 4.26). The validation data were separated into three groups. The first and second group of validation experiments (VA1 and VA2) were conducted with Walter ODMW050408T-A27 WKK25S positive octagonal inserts equipped on the milling head. The workpiece material was EN-GJS-600-3 ductile cast iron. The third group of validation experiments (VA3) was conducted with Walter SNGX1205ZNN-F67 WSP45G negative square inserts equipped on the milling head. The workpiece material was 1.7225 low-alloy steel, quenched and tempered. All experiments were conducted under dry machining conditions. Groups VA1 and VA2 are comprised from 15 machining passes and group VA3 is comprised from 16 passes. This difference of one pass is a result of the difference in workpiece width and the required passes to fully remove the material from the top face. In all groups, the passes have varying process parameters. In group VA1 the inserts were brand new, with no measurable wear being detected after the 15 machining passes. In the groups VA2 and VA3 the inserts were pre-worn from other milling operations. The flank wear was

measured using an Alicona Infinite Focus G5 cutting tool measurement system. Table 4.9 summarizes the process parameters, material and cutting tool specifications in each experiment group.



Figure 4.26 The instrumented milling head installed in the Mori Seiki machine tool

Table 4.9 Table of experiments for generalizability validation

Group	Cutting tool	Cutting tool state	Workpiece material	Process Parameter Ranges			
				Cutting speed [m/min]	Feed per tooth [mm]	Axial DoC [mm]	Radial DoC [mm]
VA1	Walter ODMW050408T-A27 WKK25S	New	EN-GJS-600-3 ductile cast iron	166-183	0.5	3	35-100

VA2	Walter ODMW050408T- A27 WKK25S	Pre-worn $V_B =$ 0.146mm	EN-GJS- 600-3 ductile cast iron	166	0.375- 0.5	3	35-100
VA3	Walter SNGX1205ZNN- F67 WSP45G	Pre-worn $V_B =$ 0.042mm	1.7225 low-alloy steel	98-121	0.125- 0.234	2-4	100

As the wear progression within each experiment group was not significant, all process data within the same group are considered to be in the same wear level. It is of interest, however, to also validate that the algorithms still perform well, considering the variation of process parameters within the group, as well as the temperature increase. Regarding the classification, the inserts in VA2 and VA3 are considered to be in the “steady-state” phase, while the inserts in VA1 are considered to be in the “break-in” phase. The cutting force and temperature data are recorded, the features described in Section 4.5 are calculated and input into the decision tree classifier (without any retraining) to validate its accuracy. Figure 4.27 presents the confusion matrix, based on the predictions of the decision tree classifier on the unknown dataset. A slight accuracy decrease can be observed, compared to the training phase, which is something to be expected. Nevertheless, the accuracy level in the unknown dataset (91%) is still acceptable for the intended application. Additionally, it can be observed from the confusion matrix that the classifier fails by predicting data from the “steady-state” phase to be in the “break-in” phase. These data come from group VA2, where there is still low flank wear and is borderline on the “steady-state” phase. In the data coming from group VA3, where the flank wear has progressed significantly, there is no misclassification.

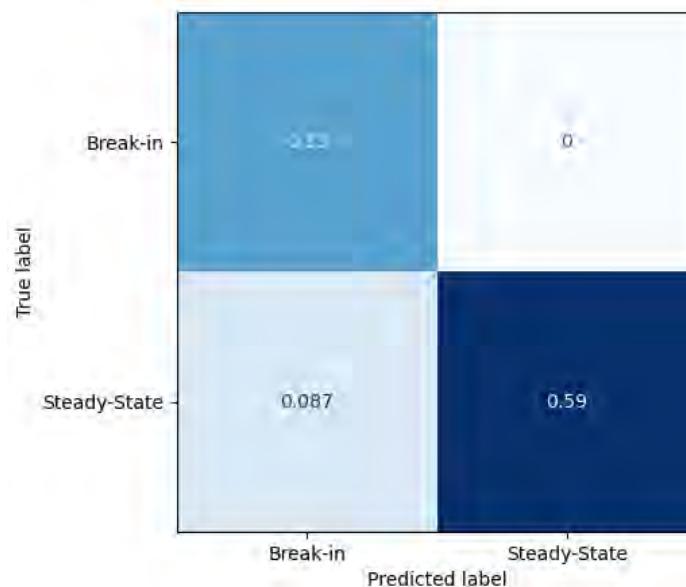


Figure 4.27 Confusion matrix of the Decision Tree classifier on the validation dataset

Table 4.10 Classification report of the Decision Tree classifier on the validation dataset

Class	Precision	Recall	F1-score
Break-In	0.79	1.00	0.88
Steady-State	1.00	0.87	0.93

Next, the performance of the Random Forest regressor is evaluated. Table 4.11 presents the results. One can observe that the performance of the regressor on the unknown dataset is quite similar to the performance on the training dataset. This can be attributed to the fact that the regressor uses an ensemble of Decision Trees, which increases its robustness over the classifier, which uses a single Decision Tree. Additionally, as it can be observed from Figure 4.28, which depicts the predicted flank wear values, compared to the nominal ones, the regressor mainly overpredicts the flank wear in the “break-in” phase. Similarly to the Decision Tree classifier, the performance of the Random Forest regressor on the unknown dataset can be considered acceptable, given its intended application.

Table 4.11 Evaluation of the prediction performance of the Random Forest regressor on the unknown dataset

Evaluation metric	Performance of regressor
Mean Squared Error (MSE)	0.0005
Root Mean Squared Error (RMSE)	0.0223
Mean Absolute Error (MAE)	0.0189

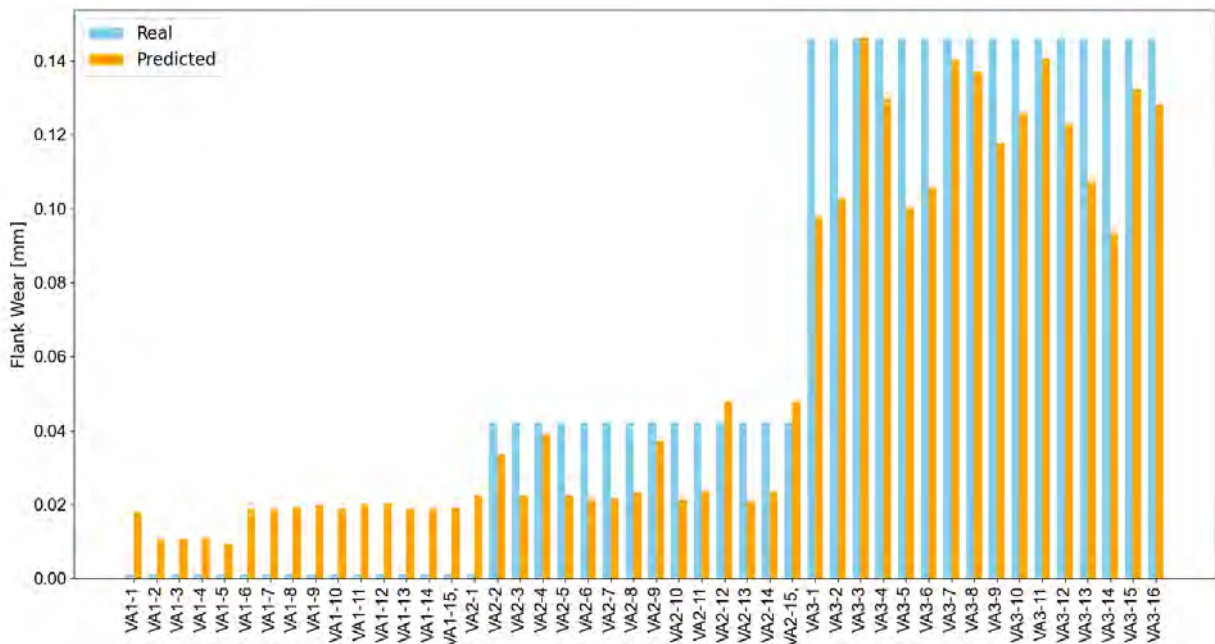


Figure 4.28 Comparison of predicted and real flank wear values in the unknown dataset

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5. CHAPTER 5. DISCUSSION AND OUTLOOK

5.1. *Summary of contributions*

Overall, the main research contribution of this thesis was to develop a methodology to support the digitalization of machining, focusing on the optimization of machining process quality, while ensuring their viability for industrial adoption. The digitalization barriers that have been targeted are the disruption of current workflow of process planners from existing digital tools, the compatibility with legacy machine tools and the integration and operation complexity. The focus of this research was the optimization of machining process quality, taking as reference the minimization of the machining error. The research was organized in three pillars: (i) minimization of machining load-induced error in robotic machining; (ii) in-process chatter detection and (iii) in-process prediction of the tool wear level. These three pillars are pain points of the machining sector and are being researched for several decades; nevertheless, there is still room for further research on the topics, especially for approaches that are closer to real industrial needs.

Regarding Pillar 1, a Multi-Body Simulation of a machining robot has been developed. This MBS was tightly interfaced with the CAM software, so that it can be automatically setup, based on the toolpaths generated and process parameters selected in the CAM. The result of this simulation is the machining-induced deformation along the toolpath. On top of this simulation, surrogate optimization strategies have been developed. Using the MBS to generate a synthetic dataset of the robot stiffness within its working volume, a twofold optimization approach has been developed. Firstly, workpiece placement optimization algorithms have been derived, in order to select the optimal position for the workpiece and orientation per machining feature, taking advantage of the two additional degrees of freedom of the rotary table. This optimization algorithms have been implemented through a Python application that incorporates a 3D viewer, where the process planner can import the CAD of the part and select the faces of the features to be machined, which is the same workflow as in CAM programming. Then, the optimal configuration for the workpiece is output and can be used by the process planner when setting up the CAM. Next, the optimization of the redundant angle of the robotic arm during 5-axis milling takes place. The optimization algorithm optimizes the toolpath in segments, considering both kinematic performance and stiffness of the robot, to ensure motion smoothness. The optimization algorithm is implemented in a Python application that, essentially, acts as an advanced post-processor, since it can directly input a file that is exported from the CAM and outputs the part program that can be directly used in the robot. All in all, this approach diminishes the disruption of the current workflow of process planners and is suitable for use in their day-to-day job. The benefits of the approach were demonstrated by

machining a real component, where improvements both in dimensional accuracy and robot vibrations have been observed, thanks to the optimization approach.

Regarding Pillar 2, an in-process, real-time chatter detection system has been developed. The system is based on self-developed monitoring setup, comprised of a low-cost, industrial accelerometer and data acquisition device. The monitoring setup is easily retrofittable in legacy equipment, supporting its industrial adoption. The connection with the robot controller to retrieve position data and spindle speed, which are synchronized by the monitoring software provides also a richer dataset for offline analysis. In order to build a lightweight, fast, yet robust approach, a lot of effort is put into feature engineering. The goal is to capture features that have physical, causal relationship with the phenomenon of interest. Analysis of the vibration signals takes place in the frequency and time domains. In the frequency domain, the energy shift from harmonic (i.e. the spindle rotation frequency and its integer multiples) to inharmonic frequencies, when the process chatters, is tracked, through the energy ratio of the inharmonic peaks of the FFT of the signal. In the time domain, the cyclostationary properties of the vibration signal are exploited and the synchronous variance is tracked. It is proven that as the signal has increases synchronous variance as the process transitions to chatter, while the cyclostationarity tends to break. By calculating just two features from the signal of each accelerometer axis, albeit carefully engineered, it was possible to develop a chatter detection system with a very high accuracy. The system is implemented in Python and incorporates a user interface to monitor the process, label datasets, configure the monitoring setup and analyze offline data. Additionally, the system is interfaced with the CAM to aid in day-to-day usage. This user interface and the way the algorithm is setup, without need to configure its parameters manually, minimizes the required user expertise and provides relevant information for the machine tool operator and process planner. Most importantly, the generalizability of the system is validated in multiple machine tools, which verifies that it can effectively be adopted and scaled in real industrial settings.

Regarding Pillar 3, an in-process tool wear level monitoring system has been developed. The system is based on an instrumented milling head, which can be directly fitted into a machine tool, through the standard tool holder interfaces, as any milling head. The cutting force and temperature data that are measured by the milling head are used for tool wear monitoring. Again, the focus is on feature engineering, which is the cornerstone of building robust AI-based monitoring systems. Using machining theory and cutting force models, it is proven that the change of cutting forces due to tool wear can be directly reflected on the cutting force coefficients. A wear indicator is proposed, based on the cutting force coefficient with the cutting temperature being also used as a corrective factor. The wear indicator has shown that the relationship between the calculated features and the phenomenon of tool wear exists, so they were used to build a Decision Tree model that classifies the wear state and a Random Forest model that predicts the actual flank wear value. The models have been exposed to new, unknown datasets coming from a different machine tool, with different

cutting inserts, workpiece material and process parameters. The models performed very well with minimal accuracy loss, thus validating their ability to generalize.

All in all, this research has managed to propose novel approaches for optimization of the machining process quality through digital tools, with proven viability for industrial adoption.

5.2. Practical Considerations for Deployment in Industrial Settings

This thesis has been written to the maximum detail possible, including also pseudocodes of algorithms, where the textual description of the working principles of the algorithm would not suffice on its own. As such, the author hopes that replication of this work is possible towards its implementation in real, industrial settings. As stated multiple times within this thesis, the goal is to enable manufacturers, and especially SMEs, to adopt digital tools in their day-to-day operations and see real benefits in terms of productivity and quality. In order to do so, there are some practical considerations that need to be taken into account.

Regarding Pillar 1, the starting point of the optimization is the MBS of the machining robot. In order to rebuild this MBS for different robotic arms, it is necessary to have knowledge of the stiffness and damping properties of the joints. For several robotic arms, such data exist in literature and, as stated in Chapter 2, it is safe to approximate these values using data from a similar robot (reach and payload) of the same manufacturer. Essentially, by examining the part numbers of the respective components (drives and reducers), one will notice that they are reused among different models of the same brand, which makes it possible to use data from one robot to another. In case that these data are not available, dedicated experiments need to be conducted. Thankfully, the literature is filled with ample approaches on how to achieve that. Nevertheless, costly equipment is usually involved in accurately determining the stiffness and damping properties. The other main aspect is the interface with the CAM software. This should be implemented in a case-by-case basis. Basic knowledge of post-processor development, however, suffices to create such interfaces between the CAM and external software, especially when the external software is self-developed.

Regarding Pillar 2, the main consideration is the measurement setup, since the rest of the methodology can be very easily replicated. The selection of sensor and data acquisition device are paramount to achieve data quality and comes at different cost ranges. The most important consideration on the sensor is to select one that has the appropriate range to measure the expected vibrations with an adequate resolution. Also, the dynamic response of the sensor (resonant frequency) needs to be taken into account, so that the process and machine tool vibrations cannot trigger it. The placement of the sensor is also paramount. The location should be chosen as close to the cutting process as possible. However, the component, where the sensor will be mounted on, should be stiff enough to properly transmit the vibrations from the cutting tool. Moreover, mounting on cast iron components of the machine tool frame should be avoided, due to its high internal

damping that will diminish the signal. Minimal to no intervention on the machine tool is always the goal, but sometimes it is not possible. In such case, small interventions on the machine tool with the help of the machine tool vendor can help in achieving a robust sensor integration. On the topic of model training, simple staircase or ramp coupons are the best approach to make the process transition from stable to chatter and can be labelled very easily. Diversity in the input dataset is key.

Regarding Pillar 3, the main consideration is again linked with the measurement setup. This work utilized an instrumented milling head and it is possible that most manufacturers will not have access to this specific equipment. However, sensory tool holders able to measure cutting force exist in the market, as well as table dynamometers. The approach of this thesis should be directly transferrable to other types of measurement setups. However, lack of temperature measurement will introduce a significant limitation. Again, considering the input dataset, diversity is key.

5.3. Limitations and Outlook

As every research effort, the work presented in this thesis has some limitations that can also drive the pathways for future research.

Regarding Pillar 1, the main limitation can be observed in the MBS of the robot. First of all, it is implemented in Simulink environment (and not in an open-source implementation), which limits its replicability. Additionally, the model does not take into account the cutting force dynamics, due to the robot vibration. This means that the loop between the current tool position (due to its vibration) and chip thickness is not closed, as is the case in the DDE describing the dynamic vibrations in the milling process. This means that the MBS cannot be used in its current form for more complex models, such as surface generation, chatter prediction or stability lobes generation.

Based on these limitations, the following future work can be suggested. First of all, the MBS, as well as the two optimization algorithms should be fully integrated with the CAM software as a plugin. This will provide the best user experience and minimize the learning curve. Also, it will make possible to directly visualize the effects of changes made by the process planner in a single visual environment. Next, the MBS should be implemented in an open-source architecture that will also allow customization of its functionalities and optimization towards calculation time. It should also incorporate the DDE that characterizes the dynamic vibrations in milling, as well as the ability to calculate the pose-dependent FRFs of the robot and, subsequently, generate the pose-dependent SLDs, which will immensely aid in process planning. Next, regarding the optimization algorithms, extensive testing on different types of geometries (e.g. freeform surfaces) and machining operations (e.g. drilling, polishing) would be important. Additionally, more criteria could be introduced in the optimization, along with the improvement of the level of detail of the model (e.g. stability, surface roughness, etc.)

Regarding Pillar 2, the main limitation is linked with the lack of a control loop for chatter suppression. Right now, the system only offers chatter detection capabilities and notifies the operator to tweak the process to stop chatter. However, this still requires expertise from the operator, in order to select the best strategy for chatter suppression. The immediate next step for Pillar 2 is closing the loop with the robot to achieve real-time chatter suppression, utilizing spindle speed control for suppression of HFC, which is mainly dependent on the spindle dynamics and feed rate control for LFC, which is mainly dependent on the robot arm dynamics. For that, a nice synergy between Pillar 1 and Pillar 2 can be made, if the MBS is extended to also generate pose-dependent SLDs. By pre-calculating SLDs in different poses within the working volume of the robot it is possible to create lookup tables that can directly guide the control loop towards taking the right direction to suppress chatter.

Regarding Pillar 3, the main limitations can be observed in the monitoring setup, which is not commercial and the lack of online implementation. As such, the first step is to test the system using different commercial data sources. Additionally, Reduced Order Modelling could be introduced for cutting temperature, in order to have a reasonable estimate for its value during the process and eliminate the need for a temperature sensor. Moreover, closure of the loop with the machine tool is critical, in order to optimize the process parameters towards minimization of the wear rate, and to stop the process when excessive wear is detected. In order to enhance the generalizability of the approach, the examination of transfer learning to eliminate performance loss, when shifting between different cutting tools, materials, etc., would be of high interest.

6. SHORT CV/PUBLICATIONS

Mr. Athanasios (Thanassis) Souflas was born in Athens, Greece on the October 4th of 1996. In 2015, he started studying Mechanical Engineering and Aeronautics the University of Patras from where he received his Diploma in June of 2021 with the grade of 8.04/10. Starting from March of 2022 he is a PhD candidate at the University of Patras.

He has been a Research Engineer at the Laboratory for Manufacturing Systems and Automation at University of Patras since 2019. During his occupation, he has been involved in a significant number of EU funded research projects, as well as with the educational activities of the Laboratory for Manufacturing Systems and Automation. In addition, he has published more than 20 peer reviewed papers in international journals and conferences, summarised hereafter.

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The research work executed during the duration of the present thesis has led to the following publications in international peer-reviewed journals and conferences.

International Journal publications

- [1] Souflas, T., Gerontas, C., Bikas, H., Stavropoulos, P. (2024) On the Optimization of Robot Machining: A Simulation-Based Process Planning Approach. *Machines* 12(8), 521 <https://doi.org/10.3390/machines12080521>
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- [3] Souflas, T., Gerontas, C., Stavropoulos, P. (2026) Combined Workpiece Placement and Posture Optimization in Robot Machining Considering Stiffness and Kinematic Performance. *The International Journal of Advanced Manufacturing Technology*. <https://doi.org/10.1007/s00170-026-17776-5>

International Conference publications

- [1] Souflas, T., Papaioannou, C., Manitaras, D., Gerontas, C., Stavropoulos, P. (2024) In-process detection of low and high frequency chatter in robot machining. *Procedia CIRP* 130, 824-829. <https://doi.org/10.1016/j.procir.2024.10.171>